Economic activity and momentum profits: further evidence

Paulo Maio Dennis Philip[1]

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[1]Maio, paulo.maio@hanken.fi, Hanken School of Economics (Department of Finance and Statistics); Philip, dennis.philip@durham.ac.uk, Durham University Business School. We thank an anonymous referee, Geert Bekaert (the editor), Ruslan Tuneshev, and participants at the Arne Ryde Workshop, University of Glasgow, Hanken School of Economics, SOFIE "Large-Scale Factor Models in Finance Conference" in Lugano, SWFA Meeting (Dallas), and the Eastern Finance Association Meeting (Pittsburgh) for helpful comments. We are grateful to Kenneth French, Amit Goyal, Sydney Ludvigson, Robert Shiller, Robert Stambaugh, and Lu Zhang for providing stock return and other financial data. Previous drafts circulated with the titles "Macro factors and equity risk premia", "Macro factors and the cross-section of stock returns", and "Economic activity and the Intertemporal CAPM". Any remaining errors are our own.

Abstract

We show that economic activity plays an important role in explaining momentum-based anomalies. A simple two-factor model containing the market and alternative indicators of economic activity as risk factors—industrial production, capacity utilization rate, retail sales, and a broad economic index—offers considerable explanatory power for the cross-section of price and industry momentum portfolios. Hence past winners enjoy higher average returns than past losers because they have larger macroeconomic risk. The model compares favorably with popular multifactor models used in the literature. Moreover, our model is consistent with Merton's Intertemporal CAPM framework, since the macro variables forecast stock market volatility and future economic activity.

Keywords: momentum; industry momentum; asset pricing; cross-section of stock returns; Intertemporal CAPM; macro risk factors; linear multifactor models; predictability of stock returns

JEL classification: E44; G10; G12

1 Introduction

The traditional price momentum anomaly refers to the evidence that stocks that had outperformed in the recent past continue to outperform in the near future, whereas stocks that underperformed continue to perform poorly (Jegadeesh and Titman (1993)). A related market anomaly is industry momentum, which refers to the evidence showing that stocks in past winning industries continue to outperform in the near future, while stocks in past losing industries continue to underperform (Moskowitz and Grinblatt (1999)). These patterns in average returns are not explained by the baseline CAPM and represent some of the most important challenges for existing asset pricing models.[1] In recent years, several studies propose asset pricing models containing macro variables (as risk factors) in an attempt to explain cross-sectional risk premia among price momentum portfolios. Specifically, Griffin, Ji, and Martin (2003) find that a restricted version of the Chen, Roll, and Ross (1986) five-factor model (which contains industrial production growth, unanticipated inflation, and the change in expected inflation) cannot explain momentum profits. In contrast, Liu and Zhang (2008) claim that the growth in industrial production helps to price the cross-section of momentum portfolios.[2] In a similar vein, Maio (2013a) presents a conditional version of the Campbell and Vuolteenaho (2004) two-factor model, in which one of the conditioning variables is the CPI inflation rate, and finds that such a factor helps to price momentum portfolios. Bansal, Dittmar, and Lundblad (2005) use the innovation to aggregate consumption growth to explain portfolios sorted on prior returns.[3]

This paper evaluates whether macroeconomic variables are valid candidates for risk factors in multifactor asset pricing models, which help to explain momentum-based anomalies. Given the failure of some of the most popular asset pricing models in the literature to price the momentum anomalies, it makes sense to investigate whether factors related to economic activity can price those portfolios. In our empirical test, we use deciles sorted on price momentum (based on 11-month prior returns) and nine portfolios sorted on industry momentum, as in Hou, Xue, and Zhang (2015). We deviate from the related literature in two major aspects. First, we incorporate the macro factors in Merton's Intertemporal CAPM (ICAPM, Merton (1973)) framework. Following previous evidence showing that some economic activity indicators are correlated with both future aggregate stock returns and market volatility (e.g., Ludvigson and Ng (2007)), these variables are a priori valid candidates for ICAPM state variables. Thus, we specify a two-factor model in which the second factor (beyond the traditional market factor) is the innovation in each of the macro variables. In

[1] Specifically, it is well known that the Fama–French three-factor model (Fama and French (1993)) is not able to price portfolios sorted on price momentum (see, for example, Fama and French (1996), Cochrane (2007a), Maio and Santa-Clara (2012), and Maio (2013a), among others). Moreover, the recent five-factor model proposed by Fama and French (2015), which adds an investment factor and a profitability factor to the three-factor model, is also unsuccessful in explaining the momentum anomaly (see, for example, Fama and French (2016), Hou, Xue, and Zhang (2016), and Maio (2017)).

[2] Liu and Zhang (2008) claim that the difference in results relative to Griffin, Ji, and Martin (2003) might be a consequence of estimating the factor loadings based on the full sample instead of rolling windows.

[3] However, it is difficult to judge the contribution of the cash-flow beta (sensitivity of individual cash flows to aggregate consumption) in terms of explaining the momentum anomaly, since their empirical test contains 10 size portfolios and 10 book-to-market portfolios, in addition to 10 momentum portfolios.

this framework, an asset that is positively correlated with changes in the state variable earns a higher risk premium than an asset that is uncorrelated with the same state variable, the reason being that the former asset does not hedge against negative shocks in future aggregate wealth, since it offers high returns when expected future returns on wealth are also high. Furthermore, following Campbell (1996) and Maio and Santa-Clara (2012), if a state variable negatively forecasts expected aggregate returns, the risk price associated with the corresponding risk factor in the ICAPM pricing equation should also be negative. On the other hand, if a state variable negatively forecasts aggregate stock volatility, the respective risk price should be positive. As shown in Maio and Santa-Clara (2012), these propositions represent additional constraints on the cross-sectional tests of the ICAPM, which are not satisfied by many of the multifactor models proposed in the empirical asset pricing literature.

Second, we use "pure" macroeconomic variables, which are directly related to economic activity; that is, we exclude variables that are based on asset prices. In fact, many of the multifactor models presented in the empirical ICAPM literature (that do not rely on portfolio-based factors) use as risk factors (transformations of) aggregate financial ratios (e.g., dividend yield, earnings yield, book-to-market ratio), bond yields (e.g., slope of the Treasury yield curve, credit risk spread), short-term interest rates (e.g., Treasury bill rate, Fed funds rate), or stock market volatility. Our objective is to evaluate whether risk factors related to economic activity can explain cross-sectional equity risk premia among momentum-sorted portfolios. Our measures of broad economic activity are the growth rate or change in industrial production (IP), capacity utilization rate (CU), retail sales (RS), and the Conference Board Coincident Economic Index (CEI). Macroeconomic variables are a natural choice for the common systematic risk factors, since they represent a direct measure of business cycle fluctuations, which affect all the firms in the economy, although to different degrees. In principle, systematic risk should be primarily captured by macro variables outside the equity market, rather than by (excess) stock returns as is the case with portfolio-based risk factors such as those used in Fama and French (1993) or Carhart (1997). In contrast to portfolio-based risk factors, macro risk factors are not likely to be "mechanically related" to the testing assets being priced, and thus the respective asset pricing models are likely to provide sharper economic content when it comes to explaining asset pricing puzzles.[4]

Our results show that the two-factor ICAPM has significant explanatory power for both the price momentum and industry momentum portfolios. On average, the specifications that perform best in pricing those portfolios are those associated with IP and CU, followed by the model based on CEI. Hence, the performance of the macro risk factors in terms of explaining momentum profits varies in a non-trivial way across factors. Another sign of the success of the model is that most of the individual pricing errors associated with both sets of portfolios are economically as well as statistically insignificant.

[4]This is especially notable in the cases of the multifactor models from Fama and French (1993) (when tested on size/book-to-market portfolios) and Carhart (1997) (when tested on size-momentum portfolios), since in these two models both the factors and the testing assets are based on the same sorting variables. In the language of Fama and French (2016), this represents "playing a home game".

The fit of the ICAPM is robust to using equal-weighted portfolios; estimating the model on a subsample that ends in 2008; using levels (rather than innovations) in the macro variables' growth as risk factors; employing a new macro factor estimated by principal component analysis; employing alternative momentum portfolios; estimating the model in covariance representation; or using alternative model evaluation metrics. By estimating an augmented model containing the four macro factors we find that three (out of these four) factors are priced in the cross-section of 19 portfolios. Furthermore, the macro model helps to price portfolios sorted on cumulative abnormal stock returns around earnings announcements (Chan, Jegadeesh, and Lakonishok (1996)).

The performance of the ICAPM is driven by the macro factors since it is well known that the market factor cannot price the momentum and industry momentum portfolios. Thus, past winners enjoy higher average returns than past losers because they have larger macroeconomic risk. This pattern in the macro factor loadings of the momentum portfolios is consistent with the theoretical models developed by Johnson (2002) and Liu and Zhang (2014). In Johnson (2002), stock returns are more sensitive to changes in expected growth in future cash flows when such expected growth is high (due to a convexity effect). To the extent that broad economic activity is strongly positively correlated with aggregate equity cash flows, and if past winners have higher expected cash flow growth than past losers, then we would expect that winners have higher loadings on macro variables than losers. Our results suggest that expected-growth risk (across the four macro factors) is greater among winner, as compared to loser stocks, in line with Johnson (2002) and the empirical evidence provided in Liu and Zhang (2008), thus explaining the pattern in the macro factor loadings. In Liu and Zhang (2014), past winners have higher expected growth (captured by the expected growth in the investment-to-capital ratio) and higher expected marginal profitability (captured by the expected sales-to-capital ratio) than past losers. Consequently, winners have a higher expected marginal benefit of investment than losers, which translates into higher expected investment returns. Since in this model investment returns are aligned with stock returns, it turns out that past winners have higher expected stock returns than past losers. Moreover, under the investment model, any cross-sectional pattern in the stock return betas associated with a given risk factor should be matched by a similar pattern in the investment return betas corresponding to that same factor. We show that both the sales-to-capital ratio and the growth in the investment-to-capital ratio (the two key components of the investment return) are more correlated with the four macro factors among past winners than among past losers, which is consistent with the pattern in the macro factor loadings among the momentum return deciles.

We compare the performance of the ICAPM with alternative multifactor models in terms of pricing the two momentum anomalies. Our results confirm that the Fama–French three- and five-factor models (Fama and French (1993, 1015)), the four-factor model proposed by Pástor and Stambaugh (2003), and the conditional CAPM proposed by Daniel and Moskowitz (2016) cannot price either set of portfolios. On the other hand, the ICAPM compares favorably with the four-factor model from Carhart (1997) and the recent four-factor model proposed by Hou, Xue, and Zhang (2015). This is especially true when we take into account the fact that the macro factors are not mechanically related to the momentum portfolios (as is the case with the UMD factor used in Carhart (1997)).

We test whether the macro variables used as risk factors in our model are able to predict the aggregate equity premium, future economic activity, or stock market volatility and uncertainty, and thus are valid state variables within Merton's ICAPM framework (see Campbell (1993, 1996), Cochrane (2005), Maio and Santa-Clara (2012), among others). The results from predictive regressions show that economic activity forecasts a significant decline in future stock market volatility as well as in future financial and macro uncertainty. Moreover, these negative slope estimates are consistent with the positive risk price estimates for the macro factors in the asset pricing tests. Further, the macro variables predict a significant improvement in future business conditions and these slopes are consistent with the positive macro risk prices within the ICAPM framework. On the other hand, the macro variables have no forecasting power for the aggregate equity premium. Thus, our simple two-factor model is consistent with the ICAPM, because the macro factors forecast a decline in future stock volatility and an increase in future economic activity, rather than a rise in the equity premium. Our results also suggest that factors that produce higher explanatory power for cross-sectional risk premia tend to be associated with macro variables that have better forecasting power for future stock volatility, macro and financial uncertainty, or economic activity. Hence, the macro model satisfies this additional consistency criteria with the ICAPM, which takes into account the relative performance of the hedging factors in both the time-series and cross-sectional dimensions.

In addition to the studies referenced above, our paper particularly relates to Liu and Zhang (2008), who use the growth in industrial production to help explain momentum portfolios. Our work differs in several dimensions. First, we use several broad measures of economic activity and show that economic activity in general, and not only industrial production in particular, helps to explain momentum profits. In particular, several dimensions of economic activity that are not highly correlated with industrial production (such as the growth in retail sales) offer significant explanatory power for the cross-section of momentum portfolios. Second, we show that the asset pricing results are consistent with Merton's ICAPM, as discussed above, thus providing a theoretical background for the estimated macro risk prices. Third, the risk factors in our model represent innovations, rather than levels, in the growth of the macro variables. Fourth, in addition to the traditional price momentum, we analyze whether economic activity can explain industry momentum and other market anomalies such as earnings momentum. We also use both value- and equal-weighted momentum portfolios in our asset pricing tests. In sum, our results largely complement and extend the results provided in Liu and Zhang (2008).

This paper proceeds as follows. In Section 2, we present our two-factor model. Section 3 describes the data, while 4 presents the main empirical results. In Section 5, we compare the performance of the ICAPM against other multifactor models. Section 6 presents evidence on the forecasting ability of the macro factors for the equity premium, economic activity, and stock volatility. Section 7 concludes.

2 The model

In this section, we present our simple two-factor asset pricing model, which represents an application of Merton's Intertemporal CAPM (ICAPM, Merton (1973)).

We define the following expected return-covariance representation of the ICAPM,

$$\mathrm{E}(R_{i,t+1} - R_{f,t+1}) = \gamma \operatorname{Cov}(R_{i,t+1} - R_{f,t+1}, RM_{t+1}) + \gamma_z \operatorname{Cov}(R_{i,t+1} - R_{f,t+1}, \widetilde{z}_{t+1}), \tag{1}$$

where $R_{i,t+1}$ is the return on asset i; $R_{f,t+1}$ denotes the risk-free rate; γ represents the coefficient of relative risk aversion (which corresponds to the (covariance) market price of risk); RM_{t+1} is the excess market return; γ_z represents the risk price associated with state-variable risk; and $\widetilde{z}_{t+1}$ denotes the innovation in the state variable, which represents a risk factor in this model. In our case, the state variable is related to economic activity.

γ_z may be interpreted as a measure of aversion to state variable/intertemporal risk and is given by the following generic expression,

$$\gamma_z \equiv -\frac{J_{Wz}(W, z, t)}{J_W(W, z, t)},$$

where W denotes total wealth, $J_W(\cdot)$ is the marginal value of wealth, and $J_{Wz}(\cdot)$ is the derivative of $J_W(\cdot)$ with respect to the state variable.

The ICAPM can be specified in the equivalent expected return-beta representation,

$$\mathrm{E}(R_{i,t+1} - R_{f,t+1}) = \lambda_M \beta_{i,M} + \lambda_z \beta_{i,z}, \tag{2}$$

where $\lambda_M = \gamma \operatorname{Var}(RM_{t+1})$ and $\lambda_z = \gamma_z \operatorname{Var}(\widetilde{z}_{t+1})$ denote the (beta) risk prices associated with the market factor and the innovation in the economic activity variable, respectively, while $\beta_{i,M}$ and $\beta_{i,z}$ denote the respective factor loadings for asset i.[5]

Following the related literature (e.g., Campbell (1996), Petkova (2006)), the innovation in the macro variable represents the residual from an AR(1) model:

$$\widetilde{z}_{t+1} \equiv z_{t+1} - \psi - \phi z_t. \tag{3}$$

The baseline CAPM (Sharpe (1964) and Lintner (1965)) is nested in the ICAPM by setting $\gamma_z = \lambda_z = 0$ in the pricing equation above; that is, the representative investor does not care about changes in future investment opportunities:

$$\mathrm{E}(R_{i,t+1} - R_{f,t+1}) = \lambda_M \beta_{i,M}. \tag{4}$$

Following Maio and Santa-Clara (2012), if a state variable positively forecasts the stock

[5] In related work, Maio and Philip (2015) specify and test a version of the Campbell-Vuolteenaho ICAPM (Campbell and Vuolteenaho (2004)), in which macro factors are included in the first-order VAR that produces the risk factors in the model (cash-flow and discount rate news).

market return (and hence, there is a positive association between the state variable and the conditional expected return), the risk price associated with the corresponding risk factor in the ICAPM cross-sectional regression should also be positive. The intuition is that if asset i is positively correlated with expected market returns (because it is positively correlated with a state variable that forecasts an increase in the future market return) it pays well when the future market return is higher in average. Hence, this asset does not provide a hedge against adverse changes in future returns on wealth for a representative risk-averse investor, and thus should earn a positive risk premium. This in turn implies a positive risk price for the non-market factor, given the assumption of a positive covariance with (the innovation in) the state variable.[6]

When future investment opportunities are measured by the second moment of aggregate returns, we have the opposite relation to that described above: if a state variable positively forecasts aggregate stock volatility, the risk price associated with the corresponding risk factor should be negative. The intuition is that if asset i forecasts an increase in future stock volatility, it offers high returns when the future aggregate volatility is higher. Since a multiperiod risk-averse investor dislikes volatility (because it represents higher uncertainty in his future wealth), such an asset does provide a hedge for changes in future investment opportunities. Consequently, it should earn a negative risk premium, which in turn implies a negative risk price.

3 Data and variables

In this section, we describe the data for the macro factors and momentum portfolios used in the asset pricing tests conducted in the subsequent section.

3.1 Macro factors

In the empirical implementation of the ICAPM, we use four alternative variables to measure broad economic activity. The first variable is the log growth in the "industrial production total index" (IP). The second proxy is the first-difference in the "capacity utilization rate" (CU). We also use the log growth in two other macro variables—"retail sales" (RS) and the Conference Board Coincident Economic Index (CEI). The original sample period is 1971:12 to 2013:12. This sample period is conditioned by the availability of the portfolio return data discussed below. The data on IP and CU are obtained from St. Louis Fed, while the data on both RS and CEI are retrieved from the Conference Board database.

Descriptive statistics presented in the online appendix show that all four economic indicators are not very persistent, especially in comparison with other macro/financial state variables typically used in the ICAPM literature. The four variables have autocorrelations below 0.50 in magnitude. Interestingly, the log growth in retail sales shows a slightly negative first-order autocorrelation (−0.20). The cross-correlations indicate that the growth in industrial production is

[6]This argument is also consistent with Campbell's version of the ICAPM (Campbell (1993, 1996)) for a risk-aversion parameter above one, since in that model the factor risk prices are increasing functions of the first-order VAR coefficients (see also Maio (2013b)).

strongly correlated with both CU (0.92) and CEI (0.81). The coincident economic index is also strongly correlated with CU, with a correlation of 0.77. In comparison, the growth in retail sales is not significantly correlated with any of the alternative economic indicators, as most correlations are around 0.20.

Table 1 presents the summary statistics for the macro factors in the ICAPM. As indicated in the previous section, each macro factor represents the innovation from an AR(1) process estimated for the corresponding macro variable. The sample is 1972:01 to 2013:12. In the construction of the macro factors, we lag the macro variables by one month in order to account for the usual time lag in the release of macroeconomic statistics, thus ensuring that when aligning with stock returns the macro factors represent publicly available information. The market factor is obtained from Kenneth French's data library. We see that the five macro factors are not persistent, as indicated by the autoregressive coefficients below 0.15 in magnitude. Moreover, the macro factors are significantly less volatile than the market equity premium, with the innovation in retail sales showing a larger volatility (above 1% per month) than the other macro factors.

The correlations displayed in Panel B indicate that the market factor shows almost no correlation with the macro factors, with correlation coefficients very close to zero in all cases. On the other hand, both $\widetilde{IP}$ and $\widetilde{CU}$ are strongly correlated (0.90), in line with the correlations estimated for the corresponding macro variables. The innovation in CEI is also significantly correlated with both $\widetilde{IP}$ and $\widetilde{CU}$, as indicated by the correlations above 0.70. In the other cases, the correlations among the macro factors are positive but below 0.50. Therefore, to a significant degree the alternative macro factors represent different dimensions of broad economic activity.

3.2 Testing assets

In the benchmark asset pricing tests conducted in the next section, we use two alternative portfolio groups. The first group represents deciles sorted on price momentum based on 11-month prior returns with a one-month holding period (MOM, see Fama and French (1996)).[7] The second group consists of nine portfolios sorted on industry momentum (IM, see Moskowitz and Grinblatt (1999)). The portfolio returns are value-weighted and correspond to those employed in Hou, Xue, and Zhang (2015). The one-month Treasury bill rate used to construct excess portfolio returns is obtained from Kenneth French's data library.

Summary statistics presented in Table 2 show that the traditional price momentum anomaly (MOM) is significantly more pervasive than industry momentum, as indicated by the average "high-minus-low" return spread earning twice the magnitude (1.17% versus 0.54% per month). However, the spread associated with MOM is also more volatile than that corresponding to IM (7.21% versus 5.09% per month). Still, the average return spread associated with MOM is statistically more significant than the IM spread (t-ratio of 3.64 versus 2.39). The correlation (untabulated) between the two return spreads is 0.78, which suggests the absence of an excessive overlap between these

[7] As discussed in the next section and in the online appendix, alternative price momentum portfolios yield similar asset pricing results.

two momentum-based anomalies.

4 Economic activity and cross-sectional momentum risk premia

In this section, we test our two-factor model on the cross-section of average returns associated with momentum portfolios.

4.1 Econometric methodology

To test our model, we employ the two-step procedure used in Jagannathan and Wang (1998), Cochrane (2005), Brennan, Wang, and Xia (2004), and Campbell and Vuolteenaho (2004), among others. Specifically, for the two-factor model, in the first step the factor loadings are estimated from the time-series multivariate regressions for each testing asset:

$$R_{i,t+1} - R_{f,t+1} = \delta_i + \beta_{i,M} RM_{t+1} + \beta_{i,z} \widetilde{z}_{t+1} + \varepsilon_{i,t+1}. \tag{5}$$

In the second step, the expected return-beta representation is estimated by a single OLS cross-sectional regression,

$$\overline{R_i - R_f} = \lambda_M \beta_{i,M} + \lambda_z \beta_{i,z} + \alpha_i, \tag{6}$$

which allows us to obtain estimates for factor risk prices $(\widehat{\lambda})$ and pricing errors $(\hat{\alpha}_i)$. In the equation above, $\overline{R_i - R_f}$ represents the average time-series excess return for asset i.[8] In the regression above, we are testing a two-factor ICAPM; that is, we include only one economic activity factor in each specification (rather than including all four economic factors simultaneously). The reasons for this are two-fold. First, since the dimension of the cross-section is relatively small, we avoid potential overfitting associated with testing a five-factor model. Second, we want to compare the pricing performance of the alternative economic factors and avoid the multicollinearity problems that arise from including the five economic betas in the cross-sectional regression. As a robustness check, we estimate a five-factor model below.

A test for the null hypothesis that the N pricing errors are jointly equal to zero (that is, the model is perfectly specified) is given by

$$\hat{\boldsymbol{\alpha}}' \widehat{\mathrm{Var}}\,(\hat{\boldsymbol{\alpha}})^{\dagger}\, \hat{\boldsymbol{\alpha}} \sim \boldsymbol{\chi}^2(N-K), \tag{7}$$

where K denotes the number of factors ($K = 2$ in the ICAPM), $\hat{\boldsymbol{\alpha}}$ is the $(N \times 1)$ vector of pricing

[8] We do not include an intercept in the cross-sectional regression, which means that an asset that has zero betas against all factors should earn a zero risk premium (relative to the risk-free rate). Excluding the intercept also allows us to prevent the multicollinearity problem (between the intercept and some of the factor betas) arising from small cross-sectional variation in those betas, which often leads to economically implausible factor risk price estimates (see Jagannathan and Wang (2007)). Moreover, the focus in this paper (as well as in most of the literature) is in explaining the cross-section of equity risk premia rather than in fitting the risk-free rate, which is of secondary relevance. Several studies follow the practice of not including an intercept when estimating the second-pass cross-sectional regression (e.g., Brennan, Wang, and Xia (2004), Campbell and Vuolteenaho (2004), Cochrane (2005) (Chapter 12), Jagannathan and Wang (2007), and Kan, Robotti, and Shanken (2013) (see their Section B.4)).

errors, and "†" stands for a pseudo inverse.

Both the t-statistics for the factor risk prices and the computation of $\mathrm{Var}(\hat{\boldsymbol{\alpha}})$ are associated with GMM-based standard errors. These standard errors can be interpreted as a generalization of the Shanken (1992) standard errors, in the sense that they relax the implicit assumption of independence between the factors and the residuals from the time-series regressions (see Cochrane (2005), Chapter 12 for details). Similarly to Shanken (1992), there is a correction for the estimation error in the factor betas from the time-series regressions. Thus, the standard errors for the risk price estimates account for the "error-in-variables" bias in the cross-sectional regression (see Cochrane (2005)). The full details are provided in the online appendix.

As an alternative to the GMM-based standard errors, we conduct a bootstrap simulation to produce more robust p-values for the tests of individual significance of the factor risk prices and also for the $\boldsymbol{\chi}^2$-test. The bootstrap simulation consists of 5,000 replications in which the excess portfolio returns and risk factor realizations are simulated (with replacement from the original sample) independently and without imposing the model's restrictions. Thus, the data-generating process is derived under the assumption that the factors are independent from the testing assets ("useless factors" as in Kan and Zhang (1999)). Moreover, the bootstrap accounts for the contemporaneous cross-correlation among the test assets, which leads to their small factor structure (see Lewellen, Nagel, and Shanken (2010) and Nagel (2013)). The full details of the bootstrap algorithm are provided in Maio and Santa-Clara (2017) (see Campbell and Vuolteenaho (2004) and Lioui and Maio (2014) for related bootstrap simulations).

In comparison to the $\boldsymbol{\chi}^2$-test, a simpler and more robust measure of the global fit of a given model for the cross-section of returns is the cross-sectional OLS coefficient of determination,

$$R^2_{OLS} = 1 - \frac{\mathrm{Var}_N(\hat{\alpha}_i)}{\mathrm{Var}_N(\overline{R_i - R_f})}, \tag{8}$$

where $\mathrm{Var}_N(\cdot)$ stands for the cross-sectional variance. This metric represents a proxy for the proportion of the cross-sectional variance of average excess returns on the testing assets explained by the factor loadings associated with a given model.[9]

Following Lewellen, Nagel, and Shanken (2010), Kan, Robotti, and Shanken (2013), and Adrian, Etula, and Muir (2014), in order to address the statistical uncertainty associated with the in-sample cross-sectional coefficient of determination, we estimate empirical p-values based on the bootstrap simulation described above. The empirical p-values represent the fractions of artificial samples in which the pseudo explanatory ratio is higher than the sample estimate. This enables us to infer how likely we are to obtain the fit found in the original data under the assumption that the corresponding asset pricing model is not true.

[9] Since we do not include an intercept in the cross-sectional regression, this R^2 measure can assume negative values. A negative estimate means that the regression including the betas performs worse than a trivial regression with just a constant. In other words, the factor betas underperform the cross-sectional average risk premium in terms of explaining cross-sectional variation in average excess returns. Similar cross-sectional R^2 metrics are employed in Jagannathan and Wang (1996), Lettau and Ludvigson (2001), Campbell and Vuolteenaho (2004), and Lioui and Maio (2014), among others.

4.2 Factor loadings

Our empirical analysis starts with a discussion of the loadings on the macro factors. Table 3 (Panel A) presents the loadings for the macro factors associated with the MOM deciles and the corresponding heteroskedasticity-robust asymptotic t-ratios (White (1980)). We can see that past losers (lower deciles) have negative betas associated with each of the macro factors, which are statistically significant at the 5% or 10% levels. On the other hand, past winners (higher deciles) show positive loadings, albeit with lower magnitude and less statistical significance. Moreover, we observe an approximate monotonic pattern in the factor loadings, as we move from the first to the last decile. The factor loadings associated with the IM portfolios, which are presented in Panel B of Table 3, show a similar pattern to the MOM deciles. The main difference is that only the extreme winner portfolios tend to have positive loadings associated with $\widetilde{IP}$, $\widetilde{CU}$, and $\widetilde{CEI}$, while the remaining portfolios produce negative loadings. However, in contrast to the MOM deciles, it turns out that the loadings on the first and last IM portfolios corresponding to $\widetilde{IP}$ and $\widetilde{CU}$ are not statistically significant at the 10% level. Overall, these results suggest that past winners have greater macroeconomic risk than past losers.

Why are past winners more sensitive to positive shocks in economic activity than past losers? One possible explanation relies on the theoretical framework of Johnson (2002). In this model, stock returns are more sensitive to changes in expected growth in future cash flows when such expected growth is high (due to a convexity effect). To the extent that broad economic activity is strongly positively correlated with aggregate equity cash flows, and if past winners have higher expected cash flow growth than past losers, then we would expect that winners have higher loadings on macro variables than losers. Liu and Zhang (2008) confirm that winners have higher expected growth in cash flows than past losers. Moreover, they show that the expected-growth risk, which corresponds to the covariance between industrial production and the component of the portfolio's return related to the portfolio's expected growth, rises almost monotonically from the first to the last momentum deciles. Although the results in Liu and Zhang (2008) are associated with IP, they should translate as well to the other macro factors used in this study.[10] In fact, the results presented in the online appendix suggest that expected-growth risk (across the four macro factors) is greater among winner, as compared to loser stocks, in line with Johnson (2002), thus explaining the pattern in the macro factor loadings.[11]

The pattern in the macro factor loadings of the momentum portfolios is also consistent with the investment-based model of Liu and Zhang (2014).[12] In their model, past winners have higher expected growth (captured by the expected growth in the investment-to-capital ratio) and higher

[10] We thank Geert Bekaert (the editor) for suggesting this analysis.

[11] Additionally, the model of Johnson (2002) should be more successful in explaining the returns of winners than the returns of losers because the convexity effect is stronger when expected growth is high. The evidence provided below largely confirms this prediction, as the pricing errors of the winner portfolios tend to have smaller magnitudes than those corresponding to the loser portfolios (which arises from the asymmetric macro factor loadings among the momentum deciles documented above).

[12] In related work, Sagi and Seasholes (2007) show that firms with lower costs and more valuable growth options have higher return autocorrelation and contribute to enhanced momentum profits.

expected marginal profitability (captured by the expected sales-to-capital ratio) than past losers. Consequently, winners have a higher expected marginal benefit of investment than losers, which translates into higher expected investment returns. Since in this model investment returns are aligned with stock returns, it turns out that past winners have higher expected stock returns than past losers. Moreover, under the investment model, any cross-sectional pattern in the stock return betas associated with a given risk factor should be matched by a similar pattern in the investment return betas corresponding to that same factor. In the online appendix, we show that both the sales-to-capital ratio and the growth in the investment-to-capital ratio (the two key components of the investment return) show a greater correlation with the four macro factors among past winners than among past losers, which is consistent with the pattern in the macro factor loadings among the momentum return deciles documented above. We should note that the investment framework of Liu and Zhang (2014) is silent about the sources of systematic risk (the stochastic discount factor is entirely exogenous in their setup). Hence, in our context, such model can only be used to explain the cross-sectional pattern in the macro factor loadings. On the other hand, the ICAPM provides a theory of the sources of systematic risk and a restriction on the hedging risk factors and associated prices of risk (see the discussion in Section 2). However, the ICAPM is silent about cross-sectional patterns in factor loadings; that is, why some types of stocks (e.g., winners versus losers) have different exposures to the risk factors (in particular the hedging factors). In that sense, these two alternative theoretical frameworks (ICAPM and investment model) complement each other in terms of providing explanations for our empirical cross-sectional results.

4.3 Testing the ICAPM

We start by presenting the estimation results for the baseline CAPM, which serves as the benchmark for the two-factor model containing the macro factors. As noted above, the ICAPM nests the standard CAPM. The results in Table 4 confirm previous evidence showing that the CAPM cannot price the momentum deciles, as the estimates for the OLS coefficients of determination are negative, and this pattern holds for both sets of momentum portfolios. This means that the model has less explanatory power than a simple model that predicts constant expected excess returns within the cross-section of MOM and IM portfolios. However, the CAPM passes the specification test (based on the empirical p-values) in the estimation with either portfolio group and also in the joint asset pricing test including the 19 portfolios. Still, this formal statistical validation of the model does not imply any economic significance, as indicated by the negative R^2 estimates.

The results for the two-factor ICAPM are presented in Table 5. We see that the ICAPM specifications based on IP, CU, and CEI have considerable explanatory power for the price momentum deciles, as indicated by the R^2_{OLS} estimates ranging between 75% (version based on CEI) and 84% (other two versions), and these point estimates are statistically significant at the 5% level. On the other hand, the model based on RS produces the lowest explanatory power among the four ICAPM specifications ($R^2_{OLS} = 48\%$). In all cases, the risk price estimates for the macro factors are positive and statistically significant, based on both types of p-value.

Turning to the industry momentum portfolios (IM), all four versions of the model produce a relatively large fit for the cross-sectional risk premia. The specifications that deliver the largest explanatory power are those associated with IP, CU, and RS, with coefficients of determination around 80%, which are statistically significant in all three cases. Thus, the specification based on retail sales has significantly larger explanatory power for the industry momentum portfolios than for the price momentum deciles. In all four models, the macro risk prices are statistically significant based on both types of standard errors when the testing assets are IM. We also see that in the estimation with either set of portfolios (MOM or IM), the two-factor model passes the specification test (based on both types of p-value) at the 5% level in all cases. Thus, unlike the case of the baseline CAPM reported above, there is a match between the formal statistical validation of the macro model ($\boldsymbol{\chi}^2$-test) and its economic significance (OLS R^2).

We also conduct joint asset pricing tests by forcing the ICAPM to price simultaneously the MOM and IM portfolios. Thus, we impose the same risk price estimates to explain both sets of portfolios. This represents a more challenging test than pricing each of these two anomalies separately, given the higher dimension of the cross-section (19 portfolios). We see that the risk price estimates corresponding to the macro factors are positive and strongly significant in all cases. The explanatory ratios are above 50%, with the largest fit being achieved for the versions associated with IP and CU (78%). These explanatory ratios are statistically significant for the four versions of the model. Moreover, the model passes the specification test in the four cases.

In sum, the results from Table 5 show that the two-factor ICAPM has significant explanatory power for both the price momentum and industry momentum portfolios. On average, the specifications that perform best in pricing those portfolios are those associated with IP and CU, followed by the model based on CEI. Hence, the performance of the macro risk factors in terms of explaining momentum profits varies in a non-trivial way across factors.

Next, we assess the explanatory power of the model over the different portfolios within a certain group (e.g., extreme past winners versus extreme losers within MOM). Figure 1 plots the pricing errors (and respective t-statistics) associated with the MOM portfolios for the four versions of the ICAPM. We see that the magnitudes of the pricing errors tend to be quite small for most deciles, and this pattern is robust across the four versions of the model. In fact, the t-statistics indicate non-statistical significance at the 5% level for most of the individual pricing errors. The few exceptions are the first decile (past losers) in the specifications based on RS and CEI, and also the third and fourth deciles in the case of the model associated with RS. These results suggest that past losers are more difficult to price than past winners by the macro model. These findings are also in line with the results above, showing that the version based on RS delivers the worst performance among the four specifications when it comes to explaining the MOM deciles.

A similar figure corresponding to the IM portfolios is provided in the online appendix. As in the case of the MOM deciles, most of the industry momentum portfolios have pricing errors that are both economically and statistically insignificant. Only for the fourth IM portfolio, and in the version based on CEI, is there statistical significance at the 5% level. These results are consistent with the evidence above showing that this specification of the macro model delivers the worst relative performance in terms of pricing the IM portfolios. As in the case of the MOM deciles, the pricing errors associated with loser portfolios have larger magnitude than those corresponding to winner portfolios, yet these estimates are insignificant at the 10% level in all four versions of the model. We also observe that the pricing errors associated with both MOM and IM present a non-monotonic pattern, in contrast with the raw average returns, thus confirming the large fit of the macro model in terms of pricing these two portfolio groups.

4.4 Decomposing momentum risk premia

The results above suggest that the innovations in economic activity drive the fit of the ICAPM in terms of pricing both momentum anomalies. To assess this proposition more clearly, we conduct an "accounting analysis" of the contribution of each factor for the fit of each version of the model. Specifically, we compute the factor risk premium (beta multiplied by risk price) for each factor and for both the first and last portfolios within each group. For example, the market risk premium associated with the first MOM decile is given by

$$\lambda_M \beta_{1,M},$$

and similarly for the macro factors.

The results for this return decomposition when the testing assets are the MOM deciles are shown in Table 6, Panels A to D. The spread in average excess returns between the first ($D1$, losers) and the last MOM decile ($D10$, winners) is -1.17% per month, which corresponds to the (symmetric of the) momentum premium in our sample. This gap must be (partially) matched by the risk premium associated with one or more of the factors in the ICAPM for this model to match the momentum anomaly. The estimates for the spread $D1 - D10$ in the market risk premium are around 0.14-0.15%, hence the spread associated with the market factor has the wrong sign, which confirms why the baseline CAPM is unsuccessful in pricing momentum profits. Consequently, the factor responsible for the success of the ICAPM in pricing the MOM deciles is the innovation in the macro factor. The spread $D1 - D10$ in the macro risk premium is above 1% in magnitude for the versions based on IP, CU, and CEI, originating gaps in pricing errors around or below 0.30% (in magnitude) per month. The exception to this pattern is the version based on RS, in which a significant portion (-0.60%) of the original gap of -1.17% is left unexplained by the two-factor ICAPM, thus confirming the lower explanatory power of this specification for the MOM deciles.

Panels E to H of Table 6 presents the accounting decomposition for the IM portfolios. The results are qualitatively similar to those associated with the MOM portfolios. The gap high-minus-low in the market risk premium assumes the wrong sign in all four cases. On the other hand, the gap in risk premia associated with the macro factors varies between -0.42% (version based on RS) and -0.62% (version based on CU), which nearly matches the original spread in average returns of -0.54% per month. The versions based on IP and CU produce the lowest gap in risk premia not explained by the model (below or around 0.06% in magnitude), which is in line with the largest fit documented above.

In sum, the results from this subsection suggest that past winners earn higher average returns than past losers because they have greater macroeconomic risk; that is, past winners are more positively correlated with innovations in economic activity.

4.5 Sensitivity analysis

In this subsection, we conduct some robustness checks to the main results discussed above. The full discussion and tabulated results are presented in the internet appendix. To keep the focus, we discuss the results only for the augmented estimation (MOM+IM).

First, we use equal-weighted portfolios, which allows us to check for the evidence showing that small caps represent the biggest challenge for asset pricing models (see Fama and French (2012, 2015)) and that momentum profits are stronger among small stocks (see Fama and French (2008)). As in the estimation with value-weighted portfolios, the performance of the ICAPM is quite positive and the macro factors are priced.

Second, we estimate the ICAPM for a subsample that ends in 2008:12. The goal is to evaluate the impact of the momentum crash that occurred in 2009 (see Barroso and Santa-Clara (2015) and Daniel and Moskowitz (2016)) on the fit of the two-factor ICAPM. This crash represents a significant negative return for the momentum strategy, which may impose a relevant challenge for asset pricing models. The results show that the 2009 momentum crash did not substantially affect the performance of the ICAPM in terms of explaining the momentum portfolios. If anything, the fit of the macro model improves when such an event is included in the analysis. This stems from the fact that there was a significant decline in economic activity during the 2007–2009 period, which matches the low (or negative) returns for the momentum strategy around the same period.

Third, we estimate the macro model by using the original macro variables (growth in economic activity) as risk factors. This is in line with the procedure adopted by Liu and Zhang (2008), who employ the growth rate in industrial production, rather than its innovation, to price momentum portfolios. The fit of the new ICAPM based on the original macro variables (growth) is similar to the benchmark ICAPM based on innovations to those variables. Thus, the way the macro factors are constructed in our benchmark specification does not seem to drive the performance of the ICAPM.

Fourth, we estimate the ICAPM by using another macro factor, which summarizes the common information in a large panel of macroeconomic indicators. Specifically, we consider a large set of 73 macroeconomic time series, originally used by Stock and Watson (2002b). To estimate the common macroeconomic factors, we use asymptotic principal component analysis, developed by Connor and Korajczyk (1986) and widely implemented for large macroeconomic panels (see Stock and Watson (2002a, 2002b), Ludvigson and Ng (2007, 2009), among others). We then pick the first factor that is statistically significant as the new macro risk factor in our two-factor model. Overall, the results for the ICAPM based on the estimated common macro factor are consistent with the results for the benchmark specifications based on observed macro factors. In particular, the new model has significant explanatory power for the MOM deciles.

Fifth, we use an alternative group of price momentum deciles (MOM*) based on six-month prior returns (see Jegadeesh and Titman (1993) and Hou, Xue, and Zhang (2015)). The asset pricing results show that the fit of the ICAPM for the MOM* portfolios is generally lower than for the MOM deciles. However, in the versions based on IP and CU, the macro model continues to deliver a significant explanatory power.

Sixth, we use alternative t-ratios for the factor risk price estimates and estimate the ICAPM in covariance representation. The performance of the two-factor model is robust to these alternative setups.

Seventh, we compute two additional metrics proposed by Kan, Robotti, and Shanken (2013) to evaluate the performance of the ICAPM: an alternative cross-sectional OLS R^2 ($\widehat{\rho}^2$ and associated specification tests) and the $\widehat{Q}_c$-statistic, which tests the null hypothesis that the pricing errors are jointly equal to zero. Overall, these two additional evaluation metrics, and associated model specification tests, provide further support for our model.

Finally, we specify and estimate an augmented five-factor model, which evaluates the joint asset pricing implications of the four macro factors for the cross-section of momentum portfolios. This model explains about 80% of the cross-sectional dispersion in risk premia among the 19 portfolios, which is significantly above the fit associated with the two-factor model based either on RS or CEI. Moreover, the risk price estimates associated with $\widetilde{IP}$, $\widetilde{CU}$, and $\widetilde{CEI}$ are significant at the 1% or 5% levels. This suggests that, despite the large correlation among these three factors, it turns out that each of these factors adds explanatory power for cross-sectional risk premia conditional on the other factors. In sum, different dimensions of economic activity provide useful information in terms of explaining momentum profits.[13]

4.6 Earnings momentum

In this section, we assess the explanatory power of the ICAPM for another market anomaly. The full analysis is presented in the online appendix.

Specifically, we use deciles sorted on the cumulative abnormal stock returns around earnings announcements (with a one-month holding period, ABR). This is also known as the post-earnings announcement drift anomaly (a variant of earnings momentum) and stems from the evidence that stocks with higher returns around earnings announcements tend to offer subsequent higher average returns than stocks with lower returns around those events (see Chan, Jegadeesh, and Lakonishok (1996) and Hou, Xue, and Zhang (2015)).

The results show that, with the exception of the version based on RS, the ICAPM has a relevant explanatory power for the value-weighted ABR deciles. Specifically, for these three specifications (IP, CU, and CEI) the R^2_{OLS} estimates are close to 50% and the ICAPM is not rejected by the specification test at the conventional levels. Moreover, the macro risk prices are

[13] We thank the referee for suggesting this analysis.

positive and statistically significant at the 1% level. Therefore, these results suggest that the ICAPM based on economic activity helps explaining the post-earnings announcement drift anomaly. This result is also consistent with previous evidence showing that the price and earnings momentum anomalies are correlated (see, for example, Chordia and Shivakumar (2006) and Novy-Marx (2015)).

5 Alternative multifactor models

To put in perspective the results obtained with the two-factor ICAPM for momentum portfolios, we estimate alternative multifactor models widely used in the empirical asset pricing literature.

5.1 Alternative models

The first model is the Fama and French (1993, 1996) three-factor model (FF3, henceforth), for a long time the most widely used model in the empirical asset pricing literature. The FF3 model can be represented in expected return-beta form as

$$\mathrm{E}\left(R_{i,t+1} - R_{f,t+1}\right) = \lambda_M \beta_{i,M} + \lambda_{SMB} \beta_{i,SMB} + \lambda_{HML} \beta_{i,HML}, \tag{9}$$

where $(\lambda_{SMB}, \lambda_{HML})$ denote the risk prices associated with the size (SMB) and value (HML) factors, respectively, and $(\beta_{i,SMB}, \beta_{i,HML})$ stand for the corresponding factor loadings for asset i.

The second model is the four-factor model from Carhart (1997) (C4), which adds a momentum factor (UMD, up-minus-down short-term past returns) to the FF3 model:

$$\mathrm{E}(R_{i,t+1} - R_{f,t+1}) = \lambda_M \beta_{i,M} + \lambda_{SMB} \beta_{i,SMB} + \lambda_{HML} \beta_{i,HML} + \lambda_{UMD} \beta_{i,UMD}. \tag{10}$$

Next, we estimate the four-factor model from Pástor and Stambaugh (2003) (PS4), which adds a stock liquidity factor (LIQ, high-minus-low liquidity) to FF3:

$$\mathrm{E}(R_{i,t+1} - R_{f,t+1}) = \lambda_M \beta_{i,M} + \lambda_{SMB} \beta_{i,SMB} + \lambda_{HML} \beta_{i,HML} + \lambda_{LIQ} \beta_{i,LIQ}. \tag{11}$$

The fourth model is the four-factor model recently proposed by Hou, Xue, and Zhang (2015) (HXZ4). This model includes an investment factor (IA, low-minus-high investment-to-assets ratio) and a profitability factor (ROE, high-minus-low return on equity) in addition to the market and size (ME) factors:

$$\mathrm{E}(R_{i,t+1} - R_{f,t+1}) = \lambda_M \beta_{i,M} + \lambda_{ME} \beta_{i,ME} + \lambda_{IA} \beta_{i,IA} + \lambda_{ROE} \beta_{i,ROE}. \tag{12}$$

Next, we estimate the five-factor model from Fama and French (2015) (FF5), which adds an investment (CMA) and a profitability (RMW) factor to FF3:

$$\mathrm{E}(R_{i,t+1} - R_{f,t+1}) = \lambda_M \beta_{i,M} + \lambda_{SMB} \beta_{i,SMB} + \lambda_{HML} \beta_{i,HML} + \lambda_{CMA} \beta_{i,CMA} + \lambda_{RMW} \beta_{i,RMW}. \tag{13}$$

We should note that although both the HXZ4 and FF5 models include investment and profitability factors, these factors are constructed in different ways in the two models (see Hou, Xue, and Zhang (2015) and Fama and French (2015) for details on the factor construction).

Finally, we estimate the conditional CAPM proposed by Daniel and Moskowitz (2016) specifically to explain momentum profits (denoted by DM2),

$$\mathrm{E}(R_{i,t+1} - R_{f,t+1}) = \lambda_M \beta_{i,M} + \lambda_{MI} \beta_{i,MI}, \tag{14}$$

where λ_{MI} and $\beta_{i,MI}$ denote the risk price and loading associated with the scaled market factor $RM_{t+1}I_t$, respectively.[14] I_t is the bear market dummy, which takes a value of one if the cumulative log market return over the previous 24 months is negative and zero otherwise. The role of the scaled factor is to account for the time-variation in the market beta of the momentum strategy documented by Daniel and Moskowitz (2016) (see also Grundy and Martin (2001)): after a bear (bull) stock market the beta of UMD is significantly negative (positive).[15]

5.2 Results

The data on SMB, HML, UMD, RMW, and CMA are obtained from Kenneth French's data library. The data on ME, IA, and ROE are retrieved from Lu Zhang, whereas the data for the liquidity factor is obtained from Robert Stambaugh's webpage. To save space, we only report the results associated with the augmented asset pricing test including the 19 portfolios.

As in Maio (2017) (see also Cochrane (2005) and Lewellen, Nagel, and Shanken (2010)), we compute the "constrained" cross-sectional R^2,

$$R_C^2 = 1 - \frac{\mathrm{Var}_N(\hat{\alpha}_{i,C})}{\mathrm{Var}_N(\overline{R_i - R_f})}, \tag{15}$$

which applies to these models where all the factors represent excess stock returns. This metric is similar to R_{OLS}^2, but is based on the pricing errors ($\hat{\alpha}_{i,C}$) from a pseudo regression that restricts the risk price estimates to be equal to the respective factor means. For example, in the case of FF3, these pricing errors are obtained from the following equation,

$$\overline{R_i - R_f} = \overline{RM}\beta_{i,M} + \overline{SMB}\beta_{i,SMB} + \overline{HML}\beta_{i,HML} + \alpha_{i,C}, \tag{16}$$

where $\overline{RM}$, $\overline{SMB}$, and $\overline{HML}$ denote the sample means of the market, size, and value factors, respectively. The constrained regression is equivalent to the time-series regression approach frequently employed in tests of factor models that contain only traded factors (e.g, Fama and French (1993, 1996, 2015, 2016), Hou, Xue, and Zhang (2015), among others).

[14] We thank Geert Bekaert (the editor) for suggesting this analysis.

[15] More specifically, after a bear equity market the market beta of the momentum factor is negative since past winners have low betas (defensive stocks that performed relatively better in the bear market) and past losers have high betas (aggressive or cyclical stocks that underperformed in the bear market). On the other hand, in a bull market past winners have high market betas while past losers exhibit low betas.

We should note that this restriction on the risk prices also applies to the conditional CAPM presented above, since $RM_{t+1}I_t$ represents a scaled return or the return on a managed portfolio (see Cochrane (2005), Chapter 8 for a detailed discussion).[16] On the other hand, it is important to note that such a restriction does not apply to our ICAPM, since the macro factors do not represent holding-period returns on traded portfolios. Thus, R^2_{OLS} represents the correct metric to assess the explanatory power of the ICAPM containing the macro factors.

The results are displayed in Table 7. At first sight, we would be tempted to conclude that most multifactor models have relevant explanatory power for both the MOM and IM portfolios. Indeed, apart from the three-factor model, the R^2_{OLS} estimates are relatively large, assuming values between 36% (PS4) and 90% (HXZ4). However, this large fit is in most cases spurious, as it is associated with implausible risk price estimates for several factors in these models. Specifically, the estimates for λ_{SMB}, λ_{HML}, λ_{LIQ}, and λ_{IA} are negative in several cases, far away from the respective factor means (which are positive by construction). In the case of λ_{MI}, we also obtain a significantly negative estimate compared to a marginal positive mean of the scaled market factor (0.05%). Consequently, when we impose the restriction that the risk price estimates should be equal to the corresponding factor means, the fit of the models drops sharply. In fact, the R^2_C estimates associated with FF3, PS4, FF5, and DM2 models are negative. This means that these multifactor models perform worse than a trivial model that predicts constant risk premia within the cross-section of momentum portfolios. These results confirm previous evidence that the Fama–French three-factor model is not able to explain the momentum anomaly (see, for example, Fama and French (1996), Maio and Santa-Clara (2012), and Maio (2013a), among others) and similar evidence holds for the five-factor model (e.g., Fama and French (2016), Hou, Xue, and Zhang (2016), and Maio (2017)). On the other hand, the weak performance of the conditional CAPM is consistent with the significant alphas reported in Daniel and Moskowitz (2016) (see their Tables 3 and 4). Consequently, only the C4 and HXZ4 models offer positive, and economically significant, explanatory power for both sets of portfolios, as indicated by the R^2_C estimates above 60%.

Nevertheless, when we compare the performance of the ICAPM (based on R^2_{OLS}) with both C4 and HXZ4 (based on R^2_C), it turns out that the ICAPM specifications associated with IP and CU outperform both the C4 and HXZ4 models when it comes to pricing the joint 19 portfolios. On the other hand, the ICAPM based on CEI has a marginally better performance than HXZ4. However, we should note that the performance of C4 is driven by the UMD factor, which is (nearly) mechanically related to the MOM deciles.

In sum, the performance of the ICAPM as compared to the best alternative multifactor models is quite favorable. This is especially true when we take into account the fact that the macro factors are not mechanically related to the momentum portfolios, as is the case with the UMD factor.

[16]See also Ferson and Schadt (1996), Ferson and Harvey (1999), and Lewellen (1999) for empirical tests of conditional factor models.

6 Macro factors and future investment opportunities

In this section, we test whether the macro variables analyzed in the previous sections are able to predict the aggregate equity premium, economic activity, or stock market volatility, and thus are valid state variables within Merton's ICAPM framework (see Campbell (1993, 1996), Cochrane (2005), Maio and Santa-Clara (2012), among others).

6.1 Equity premium prediction

To test whether each of the macro variables forecast aggregate excess market returns at multiple horizons, we conduct monthly long-horizon predictive regressions (Keim and Stambaugh (1986), Campbell (1987), Fama and French (1988, 1989)),

$$r^e_{t+1,t+q} = a_q + b_q z_t + u_{t+1,t+q}, \tag{17}$$

where $r^e_{t+1,t+q} \equiv r^e_{t+1} + ... + r^e_{t+q}$ is the continuously compounded excess market return over q periods into the future (from $t+1$ to $t+q$), and $z \equiv IP, CU, RS, CEI$ represents one of the economic activity indicators (in levels). The proxy for the market return is the value-weighted CRSP return, and to compute excess returns we subtract the one-month T-bill rate. We use forecasting horizons of 1, 3, 6, 9, 12, 24, and 36 months ahead. The statistical significance of the regression coefficients is assessed by using Hodrick (1992) t-ratios, which introduce a correction for the serial correlation in the residuals that stems from using overlapping returns. These statistics tend to have better size and power properties in finite samples than alternative asymptotic t-ratios such as those proposed by Hansen and Hodrick (1980) and Newey and West (1987) (see Hodrick (1992) and Ang and Bekaert (2007)).[17]

The results for the predictive regressions, which are displayed in the online appendix, show that in nearly all cases the economic indicators forecast a decline in the equity premium. The very few exceptions are the regressions with CU (at the one-month horizon) and RS (at $q = 9$). However, these negative slopes are largely statistically insignificant. The weak forecasting power of the macro factors for the equity premium is also illustrated by the very low R^2 estimates, which are very close to zero in all cases (around or below 2%). In sum, these results show that the economic output variables cannot forecast the equity premium at multiple horizons.[18]

[17] Some authors argue that the strong long-horizon predictability for future stock market returns documented in the literature is a consequence of the large persistence in the predictors (see, for example, Boudoukh, Richardson, and Whitelaw (2008)). However, this is not likely to be the case with the macro variables analyzed here, since they are much less persistent than the typical predictors used in the predictability literature (see the discussion in Section 3). Moreover, since the macro indicators are not related to stock prices, the shocks in the predictor are not likely to be contemporaneously correlated to the shocks in the predictive regression for stock returns, in contrast to other predictors used in the literature (see Stambaugh (1999)).

[18] Ludvigson and Ng (2007) show that macro factors estimated by factor analysis are significant predictors of the equity premium one-quarter ahead, yet they cease to be significant after controlling for standard financial predictors.

6.2 Future economic activity

In light of Roll's critique (Roll (1977)), we investigate whether current business conditions forecast a rise in future economic activity. Since the stock index is an imperfect proxy for aggregate wealth, it is likely that changes in the future return on the unobservable wealth portfolio might be positively correlated with future economic activity. Specifically, several forms of non-financial wealth, such as labor income, houses, or small businesses, are related to the business cycle, and hence, economic activity. Hence, to achieve consistency with the ICAPM framework, the macro variables should forecast a rise in future economic activity (see Boons (2016) and Cooper and Maio (2017)).

We use the Chicago FED National Activity Index ($CFED$) and the log growth in aggregate earnings (Δe) as the proxies for broad business conditions. The data on $CFED$ are obtained from the St. Louis FED, whereas the level of earnings associated with the S&P index are retrieved from Robert Shiller's webpage. We run the following univariate regressions to forecast future economic activity

$$y_{t+1,t+q} = a_q + b_q z_t + u_{t+1,t+q}, \tag{18}$$

where $y \equiv CFED, \Delta e$ and $y_{t+1,t+q} \equiv y_{t+1} + ... + y_{t+q}$ denotes the forward cumulative sum in either $CFED$ or Δe.

The results for the predictive regressions associated with $CFED$ are presented in Table 8. We can see that all four economic indicators forecast a significant increase in the index of broad economic activity at all forecasting horizons. The slopes are significant at the 1% in all cases, the sole exception being the regression with RS at the one-month horizon (in which there is significance at the 5% level). The strongest forecasting power happens at short and medium horizons ($q < 12$), with explanatory ratios around or above 20% when the predictors are IP, CU, and CEI. In comparison, RS has significantly less forecasting power than the other current economic indicators, as shown by the R^2 estimates around 5%.

The results tabulated in the online appendix show that all four economic indicators forecast a significant increase in future earnings growth at short and middle horizons. IP and CU register the largest predictive power, with R^2 estimates around 10% at short horizons, while retail sales registers the weakest forecasting performance. In sum, the results from this subsection suggest that current economic indicators forecast a significant improvement in future business conditions, which is consistent with the ICAPM framework.

6.3 Stock market volatility prediction

Next, we analyze the forecasting power of the cyclical indicators for stock market volatility. Following Maio and Santa-Clara (2012) and Paye (2012), we run predictive regressions of the type,

$$svar_{t+1,t+q} = a_q + b_q z_t + u_{t+1,t+q}, \tag{19}$$

where $svar_{t+1,t+q} \equiv svar_{t+1} + ... + svar_{t+q}$ and $svar_{t+1} \equiv \ln(SVAR_{t+1})$ is the log of the realized stock market volatility. The data on $SVAR$ are retrieved from Amit Goyal's webpage.

The results for the predictive regressions associated with stock market volatility are displayed in Table 9. All the macro variables forecast a decline in future stock volatility and this effect is strongly statistically significant (at the 1% or 5% level) in nearly all horizons. The few exceptions are CEI (at the 36-month horizon) and RS (at the one-month horizon), in which there is no significance for the predictive slopes.[19]

The economic significance of the predictability at short and middle horizons is much stronger than the predictability for the equity premium discussed above, as indicated by the R^2 estimates ranging between 4% (CU at $q = 1$) and 9% (in the regressions for CEI at several horizons).[20] The exceptions to this pattern are the regressions for RS, in which case the explanatory ratios are very close to zero at all forecasting horizons (in line with the results obtained for the equity premium regressions).

Therefore, the results from the predictive regressions for $SVAR$ show that economic activity forecasts a significant decline in future stock market volatility. Moreover, these negative slope estimates are consistent with the positive risk price estimates for the macro factors documented in the previous sections. Thus, our simple two-factor model is consistent with the ICAPM, as discussed in Section 2, because the macro factors forecast both a decline in future stock volatility and an improvement in future economic activity (and not because they forecast a rise in the aggregate equity premium).

6.4 Forecasting uncertainty

We assess whether economic activity predicts alternative measures of aggregate uncertainty. These measures are related to stock market volatility, although the correlation is far from perfect (see Bekaert, Hoerova, and Lo Duca (2013) and Jurado, Ludvigson, and Ng (2015)).

Specifically, we employ the financial and macro uncertainty proxies proposed by Jurado, Ludvigson, and Ng (2015) and Ludvigson, Ma, and Ng (2017). Financial uncertainty (U_F) represents the volatility of the unforecastable component of the future value of 147 monthly financial indicators.[21] Aggregate uncertainty (U_M) represents a similar measure constructed from 134 macroeconomic variables. The forecasting horizon associated with both uncertainty variables is one month (see Ludvigson, Ma, and Ng (2017) for details).[22] The data on both series are obtained from Sydney Ludvigson's webpage.

[19] By including the current stock market variance as an additional predictor, we still find that the slopes associated with the economic indicators are significantly negative at most forecasting horizons. The exception to this pattern are the regressions containing retail sales.

[20] This result is consistent with the evidence in Ludvigson and Ng (2007) showing that macro factors help to forecast stock volatility one quarter ahead.

[21] Bekaert, Hoerova, and Lo Duca (2013) and Bekaert and Hoerova (2016) use alternative proxies of financial uncertainty based on the VIX index. However, the VIX data is only available after 1990, and thus does not cover our sample period.

[22] We obtain similar results by using three- and 12-month uncertainty measures. Results are available upon request.

Hence, we estimate the following predictive regressions,

$$\vartheta_{F,t+1,t+q} = a_q + b_q z_t + u_{t+1,t+q}, \tag{20}$$

$$\vartheta_{M,t+1,t+q} = a_q + b_q z_t + u_{t+1,t+q}, \tag{21}$$

where $\vartheta_{F,t+1,t+q} \equiv \ln(U_{F,t+1}) + ... + \ln(U_{F,t+q})$ and similarly for $\vartheta_{M,t+1,t+q}$.

The predictability results associated with U_F are presented in Table 10. We can see that all four economic state variables forecast a significant decline in future financial uncertainty at all forecasting horizons. Only in two cases are the slopes not significant at the 10% level (in the regressions for IP and CEI at $q = 36$). Similar to the case of $SVAR$, the largest forecasting power is obtained when we use CEI as predictor (R^2 around 8-9% at short horizons).

The results concerning the multi-horizon forecasts of U_M are displayed in Table 11. There is an even stronger forecasting power relative to the case of financial uncertainty: the coefficients associated with the four real activity predictors are strongly significant (1% level) at nearly all horizons (at $q = 36$ there is significance at the 5% level in the regression for CEI). With the exception of the regressions containing RS, the explanatory ratios are above 10% at the shorter horizons ($q < 12$). Again, the largest forecasting power holds when one uses CEI as predictor (explanatory ratios around 20% at the very short horizons).

We conduct predictive regressions for an alternative measure of aggregate uncertainty employed in Ludvigson, Ma, and Ng (2017), real uncertainty (U_R). This economic uncertainty proxy is similar to U_M, except that it is constructed from a pool of 73 real activity variables (a subset of the 134 macro variables employed in the computation of U_M). This proxy focuses on the uncertainty of real economic activity by excluding other macro variables that are not directly related to economic activity (like price indices or monetary aggregates). The results tabulated in the online appendix are qualitatively similar to those corresponding to U_M as the predictive slopes are significantly negative in most cases. Yet, there is a slightly decline in forecasting power as indicated by the lower R^2 estimates (which are now marginally above 10% at short horizons).

The negative predictive slopes in the regressions for financial and macro uncertainty are interpreted in the same way as the corresponding slopes in the regressions for stock market volatility. In all cases, the results confirm consistency with the positive macro risk prices, which is in line with the ICAPM's prediction. First, an increase in financial uncertainty should represent a deterioration in future aggregate investment opportunities, similarly to an increase in stock market volatility.[23] Second, following the Roll's critique, in the same vein that the expected growth in economic activity is used as a proxy for the expected return on the unobserved market portfolio, economic volatility or uncertainty can be used as proxies for the volatility of the future return on aggregate wealth.

[23] Bekaert, Hoerova, and Lo Duca (2013) estimate uncertainty as a component of stock market volatility (the estimated conditional variance).

6.5 Quantitative implications

In the discussion above, the consistency of the macro models with the ICAPM is mostly "qualitative", that is, we compare the signs of the predictive slopes of the macro variables with the corresponding risk prices with no reference to the magnitudes of these estimates. The main reason for this is that in general one can not solve analytically for the value function $J(W, z, t)$ in the ICAPM framework, and thus, one can not obtain specific expressions for the covariance risk prices associated with the hedging factors (see Cochrane (2007b)):

$$\gamma_z \equiv -\frac{J_{Wz}(W, z, t)}{J_W(W, z, t)}.$$

Without analytical expressions for $J(\cdot)$ we can not obtain expressions for the hedging risk prices, which provide a link of the magnitudes of the risk prices to structural parameters related to shifts in stochastic investment opportunities (in addition to preference parameters like the risk aversion coefficient).

However, there should be a relationship between the magnitudes of the factor risk prices and the size of the corresponding predictive slopes, which represents a quantitative implication of the ICAPM. Specifically, a macro variable that covaries more with future investment opportunities (e.g., $svar$) will originate stronger hedging concerns (i.e., a higher magnitude of J_{Wz}), leading to a bigger size of the respective factor risk price (in comparison to a macro variable that is less correlated with future investment opportunities). Moreover, a macro variable that has larger forecasting power for future investment opportunities (as proxied by the fit of the corresponding predictive regressions) should be associated with a risk factor that contributes more to explaining cross-sectional risk premia. In addition to the sign restriction documented above, this restriction in relative magnitudes of risk prices and predictive slopes (or in models' performance) represents an additional link between the time-series and cross-sectional dimensions that should be satisfied within the ICAPM framework.

To test these propositions associated with the ICAPM, Cooper and Maio (2017) compare the magnitudes of the factor risk price estimates with the size of the predictive slopes associated with the corresponding state variables among 10 traded risk factors. In our case, we compare the performance of each two-factor macro model in the cross-section of stock returns with the performance of the predictive regressions associated with the corresponding macro state variable, across the four factors. The objective is to assess if the dispersion (among macro models) of model performance in the cross-section is matched by a similar dispersion in predictive performance in the time-series dimension.[24]

The asset pricing results in Section 4 indicate that the two-factor models based on IP and CU clearly outperform the version based on RS with explanatory ratios of 78% versus 53%. On the other hand, the results in this section indicate that the predictive performance associated with both

[24] In our case, we do not compare the magnitudes of both the risk price estimates and predictive slopes across factors (as in Cooper and Maio (2017)) since the macro factors have different measurement units (e.g., CU and IP).

IP and CU is clearly above that of RS when it comes to predict stock market volatility, financial uncertainty, or macro uncertainty. Specifically, the maximum R^2 estimates (across forecasting horizons) in the regressions for $SVAR$, U_F, and U_M are respectively 6%, 6%, and 13-16% when the predictors are either IP or CU. When we use RS as predictor, the maximum R^2 turn out to be substantially smaller: 1%, 1%, and 4% in the regressions for $SVAR$, U_F, and U_M, respectively. The results presented above also show that both IP and CU contain significantly greater forecasting power for future economic activity (Chicago Fed Index) than retail sales.

Therefore, these results suggest that hedging factors that produce higher explanatory power for cross-sectional risk premia tend to be associated with macro variables that have better forecasting power for future stock volatility, macro and financial uncertainty, or economic activity. Hence, our two-factor macro model satisfies this additional consistency criteria with the ICAPM, which takes into account the relative performance of the hedging factors in both the time-series and cross-sectional dimensions.

7 Conclusion

This paper evaluates whether macroeconomic variables are valid candidates for risk factors in multifactor asset pricing models, which help to explain momentum-based anomalies. These patterns in average returns are not explained by the baseline CAPM and represent some of the most important challenges for existing asset pricing models. We deviate from the related literature in two major aspects. First, we incorporate the macro factors in Merton's Intertemporal CAPM (ICAPM, Merton (1973)) framework. Thus, we specify a two-factor model in which the second factor (beyond the traditional market factor) is the innovation in each of the macro variables. Second, we use "pure" macroeconomic variables, which are directly related to economic activity; that is, we exclude variables that are based on asset prices. Our measures of broad economic activity are the growth rate or change in industrial production (IP), capacity utilization rate (CU), retail sales (RS), and the Conference Board Coincident Economic Index (CEI).

Our results show that the two-factor ICAPM has significant explanatory power for both price momentum and industry momentum portfolios. On average, the specifications that perform best in pricing those portfolios are those associated with IP and CU, followed by the model based on CEI. Hence, the performance of the macro risk factors in terms of explaining momentum profits varies in a non-trivial way across factors.

We compare the performance of the ICAPM with alternative multifactor models for pricing the two momentum anomalies. Our results confirm that the Fama–French three- and five-factor models and the four-factor model proposed by Pástor and Stambaugh (2003) cannot price either set of portfolios. On the other hand, the ICAPM compares favorably with the four-factor model from Carhart (1997) and the recent four-factor model proposed by Hou, Xue, and Zhang (2015). This is especially true when we take into account the fact that the macro factors are not mechanically related to the momentum portfolios, as is the case with the UMD factor used in Carhart (1997).

Finally, we test whether the macro variables used as risk factors in our model are able to predict the aggregate equity premium, economic activity, stock market volatility, and financial and macro uncertainty and thus are valid state variables within Merton's ICAPM framework. The results from predictive regressions show that economic activity forecasts a significant decline in both future stock market volatility and financial and macro uncertainty, while forecasting an improvement in future economic activity. Moreover, these slope estimates are consistent with the positive risk price estimates for the macro factors in the asset pricing tests.

Table 1: Descriptive statistics for risk factors

This table reports descriptive statistics for the risk factors associated with the ICAPM. RM is the market factor. The economic activity factors represent the innovations in industrial production growth ($\widetilde{IP}$), change in capacity utilization ($\widetilde{CU}$), retail sales growth ($\widetilde{RS}$), and the growth in the Conference Board Coincident Economic Index ($\widetilde{CEI}$). The sample is 1972:01–2013:12. ϕ designates the first-order autocorrelation coefficient. The pairwise correlations are presented in Panel B.

Panel A					
	Mean (%)	Stdev. (%)	Min. (%)	Max. (%)	ϕ
RM	0.53	4.61	−23.24	16.10	0.08
$\widetilde{IP}$	0.00	0.69	−3.85	2.54	−0.08
$\widetilde{CU}$	0.00	0.58	−2.74	2.50	−0.10
$\widetilde{RS}$	0.00	1.18	−7.21	6.89	−0.02
$\widetilde{CEI}$	0.00	0.32	−1.66	1.06	−0.14
Panel B					
	RM	$\widetilde{IP}$	$\widetilde{CU}$	$\widetilde{RS}$	$\widetilde{CEI}$
RM	1.00	0.06	0.05	0.06	0.05
$\widetilde{IP}$		1.00	0.90	0.23	0.72
$\widetilde{CU}$			1.00	0.24	0.71
$\widetilde{RS}$				1.00	0.43
$\widetilde{CEI}$					1.00

Table 2: Descriptive statistics for portfolio spreads in returns

This table reports descriptive statistics for the "high-minus-low" spreads in returns associated with portfolio (deciles) sorted on momentum (MOM) and industry momentum (IM). The portfolios are value-weighted. The sample is 1972:01–2013:12. The numbers in parentheses represent heteroskedasticity-robust t-ratios for the mean estimates, which are obtained from a regression of the return spread on an intercept. ϕ designates the first-order autocorrelation coefficient.

	Mean (%)	Stdev. (%)	Min. (%)	Max. (%)	ϕ
MOM	1.17(3.64)	7.21	−61.35	26.30	0.05
IM	0.54(2.39)	5.09	−33.33	20.27	0.05

Table 3: Betas for macro factors

This table presents the beta estimates associated with the macro factors for the momentum (MOM) and industry momentum (IM) portfolios. The economic activity factors represent the innovations in industrial production growth ($\widetilde{IP}$), change in capacity utilization ($\widetilde{CU}$), retail sales growth ($\widetilde{RS}$), and the growth in the Conference Board Coincident Economic Index ($\widetilde{CEI}$). In parentheses are presented GMM-based t-ratios. t-ratios marked with *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively. 10/9 (1) designates the extreme high (low) portfolio within each group.

	1	2	3	4	5	6	7	8	9	10
					Panel A (MOM portfolios)					
$\widetilde{IP}$	−0.86	−0.32	−0.31	−0.12	−0.09	0.04	0.24	0.24	0.08	0.23
	(−2.15**)	(−1.16)	(−1.49)	(−0.89)	(−0.78)	(0.35)	(1.92*)	(1.90*)	(0.53)	(1.08)
$\widetilde{CU}$	−0.94	−0.37	−0.40	−0.16	−0.11	−0.03	0.31	0.30	0.15	0.39
	(−2.03**)	(−1.21)	(−1.62)	(−1.02)	(−0.75)	(−0.21)	(2.10**)	(2.06**)	(0.87)	(1.53)
$\widetilde{RS}$	−0.30	−0.25	−0.28	−0.23	−0.12	−0.06	0.07	0.15	0.17	0.24
	(−1.21)	(−1.73*)	(−2.46**)	(−2.76***)	(−1.69*)	(−0.84)	(1.01)	(1.73*)	(2.15**)	(1.84*)
$\widetilde{CEI}$	−1.49	−0.84	−0.81	−0.54	−0.43	−0.48	0.28	0.37	0.30	0.74
	(−1.73*)	(−1.45)	(−1.78*)	(−1.71*)	(−1.71*)	(−2.06**)	(1.05)	(1.47)	(1.02)	(1.58)
					Panel B (IM portfolios)					
$\widetilde{IP}$	−0.34	−0.27	−0.21	−0.25	−0.10	−0.05	−0.15	0.01	0.29	
	(−1.23)	(−1.44)	(−1.26)	(−1.88*)	(−1.00)	(−0.47)	(−1.50)	(0.12)	(1.36)	
$\widetilde{CU}$	−0.46	−0.30	−0.27	−0.25	−0.10	−0.06	−0.15	0.04	0.30	
	(−1.39)	(−1.34)	(−1.43)	(−1.56)	(−0.80)	(−0.45)	(−1.28)	(0.27)	(1.31)	
$\widetilde{RS}$	−0.20	−0.25	−0.08	−0.09	−0.06	0.03	0.07	0.13	0.13	
	(−1.29)	(−2.59***)	(−1.07)	(−1.37)	(−0.93)	(0.55)	(1.08)	(1.69*)	(0.93)	
$\widetilde{CEI}$	−0.78	−0.95	−0.58	−0.75	−0.49	−0.30	−0.29	0.06	0.79	
	(−1.40)	(−2.39**)	(−1.80*)	(−2.83***)	(−2.45**)	(−1.52)	(−1.54)	(0.23)	(1.91*)	

Table 4: Factor risk premia for CAPM

This table reports the estimation and evaluation results for the standard CAPM. The estimation procedure is the two-pass regression approach. The test portfolios are value-weighted: ten portfolios sorted on momentum (MOM) and 9 portfolios sorted on industry momentum (IM). "MOM+IM" refers to a joint test including the 19 portfolios. λ_M denotes the risk price estimate (in %) for the market factor. Below the risk price estimates are displayed t-statistics based on GMM standard errors (in parentheses). The column labeled $\boldsymbol{\chi}^2$ presents the statistic (first line) and associated asymptotic p-value (in parentheses) for the test on the joint significance of the pricing errors. The column labeled R^2_{OLS} denotes the cross-sectional OLS R^2. The sample is 1972:01–2013:12. Italic, underlined, and bold t-ratios denote statistical significance at the 10%, 5%, and 1% levels, respectively. Risk price estimates marked with *, **, *** represent statistical significance at the 10%, 5%, and 1% levels, respectively, based on the empirical p-values from a bootstrap simulation. Underlined values of the χ^2 statistic mean that the model is not rejected at the 5% level based on the p-values from the bootstrap.

	λ_M	χ^2	R^2_{OLS}
MOM	0.49***	$\underline{25.61}$	−0.31
	($\underline{2.30}$)	(0.00)	
IM	0.59***	$\underline{13.80}$	−0.29
	(**2.77**)	(0.09)	
MOM+IM	0.54***	$\underline{30.00}$	−0.31
	($\underline{2.54}$)	(0.04)	

Table 5: Factor risk premia for ICAPM

This table reports the estimation and evaluation results for the two-factor ICAPM. The estimation procedure is the two-pass regression approach. The test portfolios are value-weighted: ten portfolios sorted on momentum (MOM) and 9 portfolios sorted on industry momentum (IM). "MOM+IM" refers to a joint test including the 19 portfolios. λ_M and λ_z denote the risk price estimates (in %) for the market and economic activity factors, respectively. The economic activity factors represent the innovations in industrial production growth ($\widetilde{IP}$), change in capacity utilization ($\widetilde{CU}$), retail sales growth ($\widetilde{RS}$), and the growth in the Conference Board Coincident Economic Index ($\widetilde{CEI}$). Below the risk price estimates are displayed t-statistics based on GMM standard errors (in parentheses). The column labeled $\boldsymbol{\chi}^2$ presents the statistic (first line) and associated asymptotic p-value (in parentheses) for the test on the joint significance of the pricing errors. The column labeled R^2_{OLS} denotes the cross-sectional OLS R^2. The sample is 1972:01–2013:12. Italic, underlined, and bold t-ratios denote statistical significance at the 10%, 5%, and 1% levels, respectively. Risk price estimates marked with *, **, *** represent statistical significance at the 10%, 5%, and 1% levels, respectively, based on the empirical p-values from a bootstrap simulation. Underlined values of the χ^2 statistic mean that the model is not rejected at the 5% level based on the p-values from the bootstrap. R^2_{OLS} values marked with ** and * indicate statistical significance (based on the bootstrap) at the 5% and 10% levels, respectively.

	λ_M	λ_z	χ^2	R^2_{OLS}
Panel A ($\widetilde{IP}$)				
MOM	0.60***	0.96***	<u>8.02</u>	0.84**
	(**2.81**)	(<u>2.22</u>)	(0.43)	
IM	0.70***	0.93**	<u>3.97</u>	0.79**
	(**3.10**)	(*1.93*)	(0.78)	
MOM+IM	0.65***	0.95**	<u>10.90</u>	0.78**
	(**3.03**)	(<u>2.31</u>)	(0.86)	
Panel B ($\widetilde{CU}$)				
MOM	0.58***	0.79***	<u>8.72</u>	0.84**
	(**2.74**)	(<u>2.26</u>)	(0.37)	
IM	0.71***	0.83**	<u>3.18</u>	0.88**
	(**3.11**)	(*1.88*)	(0.87)	
MOM+IM	0.64***	0.79**	<u>11.63</u>	0.78**
	(**2.99**)	(<u>2.29</u>)	(0.82)	
Panel C ($\widetilde{RS}$)				
MOM	0.58***	1.29**	<u>13.18</u>	0.48
	(**2.75**)	(<u>2.08</u>)	(0.11)	
IM	0.64***	1.27***	<u>7.14</u>	0.76*
	(**2.98**)	(<u>2.01</u>)	(0.41)	
MOM+IM	0.61***	1.30**	<u>18.70</u>	0.53*
	(**2.90**)	(<u>2.15</u>)	(0.35)	
Panel D ($\widetilde{CEI}$)				
MOM	0.64***	0.46**	<u>8.33</u>	0.75**
	(**2.92**)	(<u>2.03</u>)	(0.40)	
IM	0.71***	0.31**	<u>8.13</u>	0.68
	(**3.23**)	(<u>2.20</u>)	(0.32)	
MOM+IM	0.68***	0.40**	<u>15.44</u>	0.65**
	(**3.11**)	(<u>2.24</u>)	(0.56)	

Table 6: Accounting of risk premia

This table reports the risk premium (beta times risk price) for each factor from the ICAPM for the first and last momentum (MOM) and industry momentum (IM) portfolios. The economic activity factors represent the innovations in industrial production growth ($\widetilde{IP}$), change in capacity utilization ($\widetilde{CU}$), retail sales growth ($\widetilde{RS}$), and the growth in the Conference Board Coincident Economic Index ($\widetilde{CEI}$). E(R) denotes the average excess return for the first and last deciles, and $\overline{\alpha}$ represents the average pricing error per decile. RM and $\widetilde{z}$ denote the market and intertemporal risk factors from the ICAPM, respectively. All the values are presented in percentage points. $D1$ and $D10/D9$ denote the lowest and highest MOM/IM portfolios, respectively, and $Dif.$ denotes the difference across extreme deciles. The sample is 1972:01–2013:12.

	E(R)	RM	$\widetilde{z}$	$\bar{\alpha}$
Panel A ($\widetilde{IP}$, MOM)				
$D1$	−0.08	0.86	−0.83	−0.11
$D10$	1.09	0.71	0.22	0.16
$Dif.$	−1.17	0.15	−1.05	−0.27
Panel B ($\widetilde{CU}$, MOM)				
$D1$	−0.08	0.83	−0.75	−0.16
$D10$	1.09	0.69	0.31	0.09
$Dif.$	−1.17	0.14	−1.05	−0.25
Panel C ($\widetilde{RS}$, MOM)				
$D1$	−0.08	0.82	−0.39	−0.50
$D10$	1.09	0.68	0.31	0.10
$Dif.$	−1.17	0.14	−0.70	−0.60
Panel D ($\widetilde{CEI}$, MOM)				
$D1$	−0.08	0.90	−0.68	−0.30
$D10$	1.09	0.75	0.34	0.00
$Dif.$	−1.17	0.15	−1.02	−0.30
Panel E ($\widetilde{IP}$, IM)				
$D1$	0.39	0.81	−0.31	−0.11
$D9$	0.93	0.71	0.26	−0.05
$Dif.$	−0.54	0.10	−0.58	−0.06
Panel F ($\widetilde{CU}$, IM)				
$D1$	0.39	0.82	−0.38	−0.05
$D9$	0.93	0.72	0.24	−0.04
$Dif.$	−0.54	0.10	−0.62	−0.01
Panel G ($\widetilde{RS}$, IM)				
$D1$	0.39	0.74	−0.26	−0.10
$D9$	0.93	0.65	0.16	0.11
$Dif.$	−0.54	0.09	−0.42	−0.21
Panel H ($\widetilde{CEI}$, IM)				
$D1$	0.39	0.81	−0.24	−0.18
$D9$	0.93	0.72	0.25	−0.03
$Dif.$	−0.54	0.10	−0.49	−0.15

Table 7: Factor risk premia for alternative multifactor models

This table reports the estimation and evaluation results for alternative multifactor models. The estimation procedure is the two-pass regression approach. The test portfolios are value-weighted: ten portfolios sorted on momentum (MOM) and 9 portfolios sorted on industry momentum (IM). λ_M, λ_{SMB}, λ_{HML}, λ_{UMD}, and λ_{LIQ} denote the risk price estimates (in %) for the market, size, value, momentum, and liquidity factors, respectively. λ_{ME}, λ_{IA}, and λ_{ROE} represent the risk prices associated with the Hou–Xue–Zhang size, investment, and profitability factors, respectively. λ_{RMW} and λ_{CMA} denote the risk price estimates for the Fama–French profitability and investment factors. λ_{MI} represents the risk price for the scaled market factor in which the instrument is the cumulative log market return over the previous 24 months. Below the risk price estimates are displayed t-statistics based on GMM standard errors (in parentheses). The column labeled $\boldsymbol{\chi}^2$ presents the statistic (first line) and associated asymptotic p-value (in parentheses) for the test on the joint significance of the pricing errors. The column labeled R^2_{OLS} denotes the cross-sectional OLS R^2, while R^2_C represents the constrained cross-sectional R^2. The sample is 1972:01–2013:12. Italic, underlined, and bold t-ratios denote statistical significance at the 10%, 5%, and 1% levels, respectively. Risk price estimates marked with *, **, *** represent statistical significance at the 10%, 5%, and 1% levels, respectively, based on the empirical p-values from a bootstrap simulation. Underlined values of the χ^2 statistic mean that the model is not rejected at the 5% level based on the p-values from the bootstrap. R^2_{OLS} values marked with ** and * indicate statistical significance (based on the bootstrap) at the 5% and 10% levels, respectively.

	λ_M	λ_{SMB}	λ_{HML}	λ_{UMD}	λ_{LIQ}	λ_{ME}	λ_{IA}	λ_{ROE}	λ_{RMW}	λ_{CMA}	λ_{MI}	χ^2	R^2_{OLS}	R^2_C
1	0.73***	−0.47**	−1.09***									28.72	0.00	−0.72
	(**3.36**)	(*−1.69*)	(<u>−2.56</u>)									(0.03)		
2	0.62***	−0.02	0.07	0.56***								23.42	0.83**	0.72
	(**2.95**)	(−0.10)	(0.27)	(**2.67**)								(0.08)		
3	0.72***	0.28	−0.99*		−5.10***							<u>8.17</u>	0.36	−0.81
	(**3.18**)	(0.69)	(−1.40)		(<u>−2.01</u>)							(0.92)		
4	0.58***					0.06	−0.32	0.71***				<u>14.55</u>	0.90**	0.62
	(**2.79**)					(0.24)	(−1.29)	(**3.12**)				(0.48)		
5	0.52***	0.40	−1.15***						0.35	0.09		17.16	0.84*	−0.14
	(<u>2.44</u>)	(1.31)	(<u>−2.42</u>)						(0.95)	(0.22)		(0.25)		
6	0.61***										−0.87***	<u>31.11</u>	0.71**	−0.10
	(**2.94**)										(<u>−2.50</u>)	(0.02)		

Table 8: Long-horizon regressions for the Chicago FED Index

This table reports the results for single long-horizon regressions for the Chicago FED National Activity Index, at horizons of 1, 3, 6, 9, 12, 24, and 36 months ahead. The forecasting variables are the log industrial production growth (IP), change in capacity utilization (CU), log growth in retail sales (RS), and the log growth in the Conference Board Coincident Economic Index (CEI). The original sample is 1972:01–2013:12. For each regression, the first line shows the slope estimates, whereas the second line presents Hodrick t-ratios (in parentheses). t-ratios marked with *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively. R^2 denotes the coefficient of determination.

	$q = 1$	$q = 3$	$q = 6$	$q = 9$	$q = 12$	$q = 24$	$q = 36$
				Panel A (IP)			
b_q	69.50	193.52	311.78	399.20	446.94	425.42	344.97
	(5.45***)	(6.81***)	(6.84***)	(7.10***)	(7.04***)	(6.11***)	(4.78***)
R^2	0.26	0.28	0.22	0.18	0.14	0.05	0.02
				Panel B (CU)			
b_q	76.39	218.22	353.63	455.86	520.15	527.43	440.99
	(5.26***)	(6.46***)	(6.78***)	(7.17***)	(7.19***)	(6.58***)	(5.43***)
R^2	0.22	0.26	0.20	0.17	0.14	0.06	0.03
				Panel C (RS)			
b_q	12.25	52.51	92.45	123.29	157.77	202.75	182.38
	(2.41**)	(5.21***)	(6.61***)	(7.20***)	(7.40***)	(7.12***)	(6.52***)
R^2	0.02	0.06	0.05	0.05	0.05	0.03	0.02
				Panel D (CEI)			
b_q	156.90	457.54	759.50	967.11	1142.65	1082.76	787.19
	(6.58***)	(7.66***)	(7.70***)	(7.70***)	(7.49***)	(6.04***)	(4.10***)
R^2	0.30	0.36	0.29	0.24	0.21	0.08	0.03

Table 9: Long-horizon regressions for the stock market variance

This table reports the results for single long-horizon regressions for the monthly log stock market variance, at horizons of 1, 3, 6, 9, 12, 24, and 36 months ahead. The forecasting variables are the log industrial production growth (IP), change in capacity utilization (CU), log growth in retail sales (RS), and the log growth in the Conference Board Coincident Economic Index (CEI). The original sample is 1972:01–2013:12. For each regression, the first line shows the slope estimates, whereas the second line presents Hodrick t-ratios (in parentheses). t-ratios marked with *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively. R^2 denotes the coefficient of determination.

	$q=1$	$q=3$	$q=6$	$q=9$	$q=12$	$q=24$	$q=36$
				Panel A (IP)			
b_q	−24.90	−74.43	−133.24	−188.57	−218.33	−229.53	−133.82
	(−3.20***)	(−4.60***)	(−5.10***)	(−5.69***)	(−5.78***)	(−4.78***)	(−2.49**)
R^2	0.05	0.06	0.06	0.06	0.05	0.02	0.00
				Panel B (CU)			
b_q	−26.03	−83.41	−156.55	−226.92	−274.21	−368.13	−352.78
	(−3.46***)	(−4.91***)	(−5.64***)	(−6.42***)	(−6.82***)	(−7.00***)	(−6.52***)
R^2	0.04	0.05	0.06	0.06	0.05	0.03	0.02
				Panel C (RS)			
b_q	−4.59	−19.27	−39.02	−59.40	−72.28	−85.27	−67.09
	(−1.55)	(−3.61***)	(−5.01***)	(−5.69***)	(−5.89***)	(−5.11***)	(−3.37***)
R^2	0.00	0.01	0.01	0.01	0.01	0.01	0.00
				Panel D (CEI)			
b_q	−61.09	−192.96	−353.79	−487.63	−597.76	−589.60	−242.07
	(−4.34***)	(−5.77***)	(−6.24***)	(−6.53***)	(−6.51***)	(−4.50***)	(−1.53)
R^2	0.06	0.09	0.09	0.09	0.08	0.02	0.00

Table 10: Long-horizon regressions for financial uncertainty

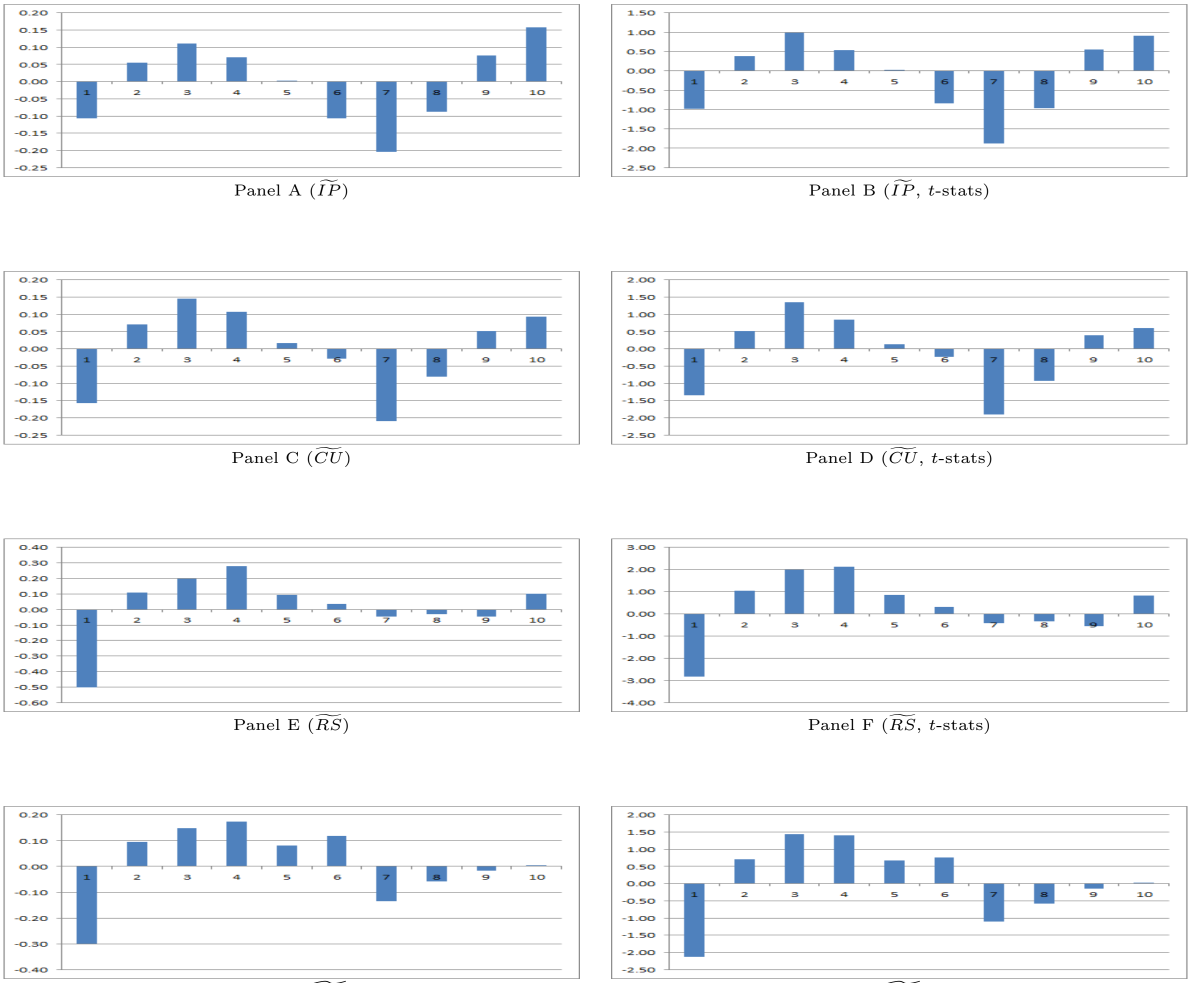
This table reports the results for single long-horizon regressions for the monthly log financial uncertainty, at horizons of 1, 3, 6, 9, 12, 24, and 36 months ahead. The forecasting variables are the log industrial production growth (IP), change in capacity utilization (CU), log growth in retail sales (RS), and the log growth in the Conference Board Coincident Economic Index (CEI). The original sample is 1972:01–2013:12. For each regression, the first line shows the slope estimates, whereas the second line presents Hodrick t-ratios (in parentheses). t-ratios marked with *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively. R^2 denotes the coefficient of determination.

	$q=1$	$q=3$	$q=6$	$q=9$	$q=12$	$q=24$	$q=36$
				Panel A (IP)			
b_q	−5.94	−16.31	−29.15	−39.60	−47.55	−45.97	−6.00
	(−3.82***)	(−4.86***)	(−5.21***)	(−5.56***)	(−5.74***)	(−4.46***)	(−0.55)
R^2	0.06	0.05	0.04	0.04	0.03	0.01	0.00
				Panel B (CU)			
b_q	−6.96	−19.65	−36.49	−51.64	−64.78	−86.01	−69.69
	(−4.18***)	(−5.21***)	(−5.91***)	(−6.63***)	(−7.17***)	(−7.77***)	(−6.05***)
R^2	0.06	0.05	0.05	0.04	0.04	0.02	0.01
				Panel C (RS)			
b_q	−1.83	−5.47	−10.06	−14.34	−17.28	−20.98	−15.27
	(−2.70***)	(−4.66***)	(−5.78***)	(−6.48***)	(−6.33***)	(−5.63***)	(−3.76***)
R^2	0.01	0.01	0.01	0.01	0.01	0.00	0.00
				Panel D (CEI)			
b_q	−15.31	−42.45	−75.27	−100.04	−122.95	−95.35	32.87
	(−5.23***)	(−5.99***)	(−6.16***)	(−6.21***)	(−6.12***)	(−3.43***)	(1.06)
R^2	0.09	0.08	0.06	0.05	0.04	0.01	0.00

Table 11: Long-horizon regressions for macro uncertainty

This table reports the results for single long-horizon regressions for the monthly log macro uncertainty, at horizons of 1, 3, 6, 9, 12, 24, and 36 months ahead. The forecasting variables are the log industrial production growth (IP), change in capacity utilization (CU), log growth in retail sales (RS), and the log growth in the Conference Board Coincident Economic Index (CEI). The original sample is 1972:01–2013:12. For each regression, the first line shows the slope estimates, whereas the second line presents Hodrick t-ratios (in parentheses). t-ratios marked with *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively. R^2 denotes the coefficient of determination.

	$q=1$	$q=3$	$q=6$	$q=9$	$q=12$	$q=24$	$q=36$
				Panel A (IP)			
b_q	−7.03	−20.62	−38.33	−51.70	−60.48	−65.03	−43.81
	(−5.34***)	(−6.87***)	(−7.88***)	(−8.51***)	(−8.66***)	(−7.91***)	(−5.15***)
R^2	0.16	0.16	0.14	0.12	0.09	0.03	0.01
				Panel B (CU)			
b_q	−7.42	−22.02	−41.55	−56.72	−67.08	−77.39	−57.40
	(−5.23***)	(−6.47***)	(−7.64***)	(−8.43***)	(−8.67***)	(−8.29***)	(−6.02***)
R^2	0.13	0.13	0.12	0.10	0.08	0.03	0.01
				Panel C (RS)			
b_q	−2.02	−6.07	−11.70	−16.91	−20.96	−29.19	−27.61
	(−3.88***)	(−5.98***)	(−7.61***)	(−8.58***)	(−8.76***)	(−8.97***)	(−8.12***)
R^2	0.03	0.04	0.03	0.03	0.03	0.02	0.01
				Panel D (CEI)			
b_q	−16.28	−47.29	−87.41	−116.40	−141.50	−133.31	−57.41
	(−6.69***)	(−7.56***)	(−8.26***)	(−8.55***)	(−8.50***)	(−6.37***)	(−2.51**)
R^2	0.20	0.19	0.17	0.14	0.11	0.03	0.00



Panel A ($\widetilde{IP}$) Panel B ($\widetilde{IP}$, t-stats)

Panel C ($\widetilde{CU}$) Panel D ($\widetilde{CU}$, t-stats)

Panel E ($\widetilde{RS}$) Panel F ($\widetilde{RS}$, t-stats)

Panel G ($\widetilde{CEI}$) Panel H ($\widetilde{CEI}$, t-stats)

Figure 1: Individual pricing errors: MOM portfolios

This figure plots the pricing errors (in % per month, Panels A, C, E, and G), and respective t-statistics (Panels B, D, F, and H) of the momentum (MOM) portfolios associated with the ICAPM. The economic activity factors represent the innovations in industrial production growth ($\widetilde{IP}$), change in capacity utilization ($\widetilde{CU}$), retail sales growth ($\widetilde{RS}$), and the growth in the Conference Board Coincident Economic Index ($\widetilde{CEI}$). The pricing errors are obtained from an OLS cross-sectional regression of average excess returns on factor betas. 10 (1) designates the extreme high (low) momentum portfolio.

References

Adrian, T., E. Etula, and T. Muir, 2014, Financial intermediaries and the cross-section of asset returns, Journal of Finance 69, 2557–2596.

Ang, A., and G. Bekaert, 2007, Stock return predictability: Is it there? Review of Financial Studies 20, 651–708.

Bansal, R., R. Dittmar, and C. Lundblad, 2005, Consumption, dividends, and the cross section of equity returns, Journal of Finance 60, 1639–1672.

Barroso, P., and P. Santa-Clara, 2015, Momentum has its moments, Journal of Financial Economics 116, 111–120.

Bekaert, G., and M. Hoerova, 2016, What do asset prices have to say about risk appetite and uncertainty? Journal of Banking and Finance 67, 103–118.

Bekaert, G., M. Hoerova, and M. Lo Duca, 2013, Risk, uncertainty and monetary policy, Journal of Monetary Economics 60, 771–788.

Boons, M., 2016, State variables, macroeconomic activity and the cross-section of individual stocks, Journal of Financial Economics 119, 489–511.

Boudoukh, J., M. Richardson, and R.F. Whitelaw, 2008, The myth of long-horizon predictability, Review of Financial Studies 21, 1577–1605.

Brennan, M.J., A.W. Wang, and Y. Xia, 2004, Estimation and test of a simple model of intertemporal capital asset pricing, Journal of Finance 59, 1743–1775.

Campbell, J.Y., 1987, Stock returns and the term structure, Journal of Financial Economics 18, 373–399.

Campbell, J.Y., 1993, Intertemporal asset pricing without consumption data, American Economic Review, 83, 487–512.

Campbell, J.Y., 1996, Understanding risk and return, Journal of Political Economy 104, 298–345.

Campbell, J.Y., and T. Vuolteenaho, 2004, Bad beta, good beta, American Economic Review 94, 1249–1275.

Carhart, M.M., 1997, On persistence in mutual fund performance, Journal of Finance 52, 57–82.

Chan, L., N. Jegadeesh, and J. Lakonishok, 1996, Momentum strategies, Journal of Finance 51, 1681–1713.

Chen, N. F., R. Roll, and S.A. Ross, 1986, Economic forces and the stock market, Journal of Business 59, 383–403.

Chordia, T., and L. Shivakumar, 2006, Earnings and price momentum, Journal of Financial Economics 80, 627–656.

Cochrane, J.H., 2005, Asset pricing (revised edition), Princeton University Press.

Cochrane, J.H., 2007a, Financial Markets and the real economy, in Rajnish Mehra, Ed. Handbook of the Equity Premium, Elsevier 237–325.

Cochrane, J.H., 2007b, Portfolio theory, Working paper, University of Chicago.

Connor, G., and R.A. Korajczyk, 1986, Performance measurement with the arbitrage pricing theory: a new framework for analysis, Journal of Financial Economics 15, 373–394.

Cooper, I., and P. Maio, 2017, Asset growth, profitability, and investment opportunities, Working paper, Norwegian Business School.

Daniel, K., and T.J. Moskowitz, 2016, Momentum crashes, Journal of Financial Economics 122, 221–247.

Fama, E.F., and K.R. French, 1988, Dividend yields and expected stock returns, Journal of Financial Economics 22, 3–25.

Fama, E.F., and K.R. French, 1989, Business conditions and expected returns on stocks and bonds, Journal of Financial Economics 25, 23–49.

Fama, E.F., and K.R. French, 1993, Common risk factors in the returns on stocks and bonds, Journal of Financial Economics 33, 3–56.

Fama, E.F., and K.R. French, 1996, Multifactor explanations of asset pricing anomalies, Journal of Finance 51, 55–84.

Fama, E.F., and K.R. French, 2008, Dissecting anomalies, Journal of Finance 63, 1653–1678.

Fama, E.F., and K.R. French, 2012, Size, value, and momentum in international stock returns, Journal of Financial Economics 105, 457–472.

Fama, E.F., and K.R. French, 2015, A five-factor asset pricing model, Journal of Financial Economics 116, 1–22.

Fama, E.F., and K.R. French, 2016, Dissecting anomalies with a five-factor model, Review of Financial Studies 29, 69–103.

Ferson, W.E., and C.R. Harvey, 1999, Conditioning variables and the cross section of stock returns, Journal of Finance 54, 1325–1360.

Ferson, W.E., and R.W. Schadt, 1996, Mesauring fund strategy and performance in changing economic conditions, Journal of Finance 51, 425–461.

Griffin, J.M., X. Ji, and J.S. Martin, 2003, Momentum investing and business cycle risk: evidence from pole to pole, Journal of Finance 58, 2515–2547.

Grundy, B., and J.S. Martin, 2001, Understanding the nature of the risks and the source of the rewards to momentum investing, Review of Financial Studies 14, 29–78.

Hansen, L.P., and R.J. Hodrick, 1980, Forward exchange rates as optimal predictors of future spot rates: An econometric analysis, Journal of Political Economy 88, 829–853.

Hodrick, R.J., 1992, Dividend yields and expected stock returns: Alternative procedures for inference and measurement, Review of Financial Studies 5, 357–386.

Hou, K., C. Xue, and L. Zhang, 2015, Digesting anomalies: an investment approach, Review of Financial Studies 28, 650–705.

Hou, K., C. Xue, and L. Zhang, 2016, A comparison of new factor models, Working paper, Ohio State University.

Jagannathan, R., and Y. Wang, 2007, Lazy investors, discretionary consumption, and the cross-section of stock returns, Journal of Finance 62, 1623–1661.

Jagannathan, R., and Z. Wang, 1996, The conditional CAPM and the cross-section of expected returns, Journal of Finance 51, 3–53.

Jagannathan, R., and Z. Wang, 1998, An asymptotic theory for estimating beta-pricing models using cross-sectional regressions, Journal of Finance 53, 1285–1309.

Jegadeesh, N., and S. Titman, 1993, Returns to buying winners and selling losers: Implications for stock market efficiency, Journal of Finance 48, 65–91.

Johnson, T.C., 2002, Rational momentum effects, Journal of Finance 57, 585–608.

Jurado, K., S.C. Ludvigson, and S. Ng, 2015, Measuring uncertainty, American Economic Review 105, 1177–1216.

Kan, R., C. Robotti, and J. Shanken, 2013, Pricing model performance and the two-pass cross-sectional regression methodology, Journal of Finance 68, 2617–2649.

Kan, R., and C. Zhang, 1999, Two-pass tests of asset pricing models with useless factors, Journal of Finance 54, 203–235.

Keim, D.B., and R.F. Stambaugh, 1986, Predicting returns in the stock and bond markets, Journal of Financial Economics 17, 357–390.

Lettau, M., and S.C. Ludvigson, 2001, Resurrecting the (C)CAPM: A cross sectional test when risk premia are time-varying, Journal of Political Economy 109, 1238–1287.

Lewellen, J., 1999, The time-series relations among expected return, risk, and book-to-market, Journal of Financial Economics 54, 5–43.

Lewellen, J., S. Nagel, and J. Shanken, 2010, A skeptical appraisal of asset-pricing tests, Journal of Financial Economics 96, 175–194.

Lintner, J., 1965, The valuation of risk assets and the selection of risky investments in stock portfolios and capital budgets, Review of Economics and Statistics 47, 13–37.

Lioui, A., and P. Maio, 2014, Interest rate risk and the cross-section of stock returns, Journal of Financial and Quantitative Analysis 49, 483–511.

Liu, L.X., and L. Zhang, 2008, Momentum profits, factor pricing, and macroeconomic risk, Review of Financial Studies 21, 2417–2448.

Liu, L.X., and L. Zhang, 2014, A neoclassical interpretation of momentum, Journal of Monetary Economics 67, 109–128.

Ludvigson, S.C., S. Ma, and S. Ng, 2017, Uncertainty and business cycles: Exogenous impulse or endogenous response? Working paper, New York University.

Ludvigson, S.C., and S. Ng, 2007, The empirical risk-return relation: A factor analysis approach, Journal of Financial Economics 83, 171–222.

Ludvigson, S.C., and S. Ng, 2009, Macro factors in bond risk premia, Review of Financial Studies 22, 5027–5067.

Maio, P., 2013a, Intertemporal CAPM with conditioning variables, Management Science 59, 122–141.

Maio, P., 2013b, Return decomposition and the Intertemporal CAPM, Journal of Banking and Finance 37, 4958–4972.

Maio, P., 2017, Do traded risk factors outperform non-traded factors? Working paper, Hanken School of Economics.

Maio, P., and D. Philip, 2015, Macro variables and the components of stock returns, Journal of Empirical Finance 33, 287–308.

Maio, P., and P. Santa-Clara, 2012, Multifactor models and their consistency with the ICAPM, Journal of Financial Economics 106, 586–613.

Maio, P., and P. Santa-Clara, 2017, Short-term interest rates and stock market anomalies, Journal of Financial and Quantitative Analysis 52, 927–961.

Merton, R.C., 1973, An intertemporal capital asset pricing model, Econometrica 41, 867–887.

Moskowitz, T.J., and M. Grinblatt, 1999, Do industries explain momentum? Journal of Finance 54, 1249–1290.

Nagel, S., 2013, Empirical cross-sectional asset pricing, Annual Review of Financial Economics 5, 167–199.

Newey, W.K., and K.D. West, 1987, A simple, positive semi-definite, heteroskedasticity and autocorrelation consistent covariance matrix, Econometrica 55, 703–708.

Novy-Marx, R., 2015, Fundamentally, momentum is fundamental momentum, Working paper, University of Rochester.

Pástor, L., and R.F. Stambaugh, 2003, Liquidity risk and expected stock returns, Journal of Political Economy 111, 642–684.

Paye, B.S., 2012, 'Déjà vol': Predictive regressions for aggregate stock market volatility using macroeconomic variables, Journal of Financial Economics 106, 527–546.

Petkova, R., 2006, Do the Fama-French factors proxy for innovations in predictive variables? Journal of Finance, 61, 581–612.

Roll, R., 1977, A critique of the asset pricing theory's tests: Part I: On past and potential testability of the theory, Journal of Financial Economics 4, 129–176.

Sagi, J.S., and M.S. Seasholes, 2007, Firm-specific attributes and the cross-section of momentum, Journal of Financial Economics 84, 389–434.

Shanken, J., 1992, On the estimation of beta pricing models, Review of Financial Studies 5, 1–34.

Sharpe, W.F., 1964, Capital asset prices: A theory of market equilibrium under conditions of risk, Journal of Finance 19, 425–442.

Stambaugh, R.F., 1999, Predictive regressions, Journal of Financial Economics 54, 375–421.

Stock, J.H., and M.W. Watson, 2002a, Forecasting using principal components from a large number of predictors, Journal of the American Statistical Association 97, 1167–1179.

Stock, J.H., and M.W. Watson, 2002b, Macroeconomic forecasting using diffusion indexes, Journal of Business and Economic Statistics 20, 147–162.

White, H., 1980, A heteroskedasticity-consistent covariance matrix estimator and a direct test for heteroskedasticity, Econometrica 48, 817–838.